# Daily schedule changes in the automated vehicle era
## Uncovering the heterogeneity behind the veil of low survey commitment

Debbaghi, Fatima-Zahra; Kroesen, M.; de Vries, G.; Pudane, B.

**DOI**
10.1016/j.tra.2024.104006

**Publication date**
2024

**Document Version**
Final published version

**Published in**
Transportation Research Part A: Policy and Practice

**Citation (APA)**
Debbaghi, F.-Z., Kroesen, M., de Vries, G., & Pudane, B. (2024). Daily schedule changes in the automated vehicle era: Uncovering the heterogeneity behind the veil of low survey commitment. *Transportation Research Part A: Policy and Practice*, *182*, 1-22. Article 104006. https://doi.org/10.1016/j.tra.2024.104006

Transportation Research Part A 182 (2024) 104006

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

# Daily schedule changes in the automated vehicle era: Uncovering the heterogeneity behind the veil of low survey commitment

Fatima-Zahra Debbaghi [a,*], Maarten Kroesen [b], Gerdien de Vries [b], Baiba Pudāne [b]

[a] *MOBI Electromobility Research Centre, Vrije Universiteit Brussel, Brussels, Belgium*
[b] *Faculty of Technology, Policy, and Management, Delft University of Technology, Delft, The Netherlands*

A R T I C L E  I N F O

Dataset link: https://data.4tu.nl/datasets/141522d5-84a8-4ec7-a362-d01ef2c75b7a

*Keywords:*
Automated vehicles
Time use
Activity schedules
On-board activities
Latent class clustering

A B S T R A C T

Automated vehicles (AVs) may transform not only our travel experience but our complete daily schedules. This study analyses the data from an interactive stated activity-travel survey using latent class cluster analysis to uncover the types and prevalence of schedule changes with AVs. The analysis reveals that the majority of respondents expected little to no changes in their schedules. Importantly however, these responses are correlated with low commitment to the survey, evident in unrealistically short response times to non-central survey parts and simpler representations of their current schedules. The remaining responses reveal significant and varied changes in activities on board and outside travel, and in commute departure times. We conclude that the prevalence of schedule changes may be underestimated in our and possibly other AV studies due to low survey commitment. Our findings also highlight diverse potential motivations behind schedule changes with AVs: while some travellers may desire to free up time for other activities during the day (*time saving*), others may satisfy an unmet activity need by engaging in on-board activities (*time spending*). Considering this heterogeneity is crucial in endeavours to quantify the total benefits and costs that automated vehicles will bring to their users.

## 1. Introduction

Automated vehicles (AVs) will take away, or at least reduce, driving responsibility from humans, and with that, they are expected to bring about several advantages in comparison to existing modes of transport. By removing the unpredictable nature of the human factor, crashes are reduced, traffic flow is more efficient, and congestion may be reduced overall (though mostly in high penetration rates, and the congestion effects depend on any induced travel) (Anderson et al., 2014; Fagnant and Kockelman, 2015). In addition, private automated vehicles are expected to allow travellers to use the travel time for activities unrelated to the driving task, which has been associated with more enjoyable travel in public transit modes (Ettema and Verschuren, 2007; Frei et al., 2015). With automated vehicles promising similar activity freedom as is available on public transport, the experience of car travel may improve greatly, although some may regret the lost freedom of controlling the vehicle. However, whether these benefits are achieved is highly uncertain and dependent on how travellers make use of the travel time (Singleton, 2019; Fraedrich et al., 2015).

The general expectation in research is that people would travel more with autonomous vehicles (Fagnant and Kockelman, 2014; Childress et al., 2015; Hörl et al., 2016). This expectation stems largely from the assumption that the penalty associated with the travel time would decrease, as a result of the ability of AV users to engage in productive or relaxing activities during travel (Zmud et al., 2016).[1] In other words, multitasking during travel is assumed to reduce the disutility of the travel time. While this approach

* Correspondence to: Vrije Universiteit Brussel, Pleinlaan 2, 1050, Brussels, Belgium.
*E-mail address:* fatima-zahra.debbaghi@vub.be (F.-Z. Debbaghi).

[1] Most sources refer to this penalty as the value of travel time (savings) (Auld et al., 2017; Kröger et al., 2019), but the term is not strictly applicable to simulation studies.

https://doi.org/10.1016/j.tra.2024.104006
Received 12 April 2023; Received in revised form 30 November 2023; Accepted 8 February 2024
Available online 5 March 2024

still sees the travel time as a “lost time” to the travellers, the losses are assumed to be lower (Lyons and Urry, 2005). This assumption is then the main driver of the expected effects of AVs, including the increased travel demand (Singleton, 2019).

However, studies are also increasingly acknowledging the limitations of the travel time penalty approach, claiming that it oversimplifies the potential activity-travel effects of new on-board activities (Mokhtarian, 2018; Pudāne et al., 2018). Thereby, increasing number of studies have started surveying daily activity-travel rearrangements directly. One such study is Kim et al. (2020). Kim et al. (2020) recorded travellers’ assessment of specified types of activity-travel changes and found an interest in increased time flexibility, especially among the young population. On the other hand, Pudāne et al. (2021)’s study found a high interest in various activities on-board, especially among participants with higher education levels. A limitation of this study, however, is the aggregate nature of its analysis, whereby unobserved heterogeneity among travellers is ‘averaged’ in each group (Pudāne et al., 2021).

The present study contributes to this literature by empirically and quantitatively investigating the daily schedule changes with AVs. We reuse the data of Pudāne et al. (2021), while focusing on the heterogeneity among the travellers. That is, while Pudāne et al. (2021) revealed that respondents of similar socio-demographic backgrounds had only few commonalities in their envisioned changes in stationary activity schedules (defined as activities conducted outside of travel (in stationary or not moving locations)), we answer the question of whether there are groups of respondents that envision similar changes in stationary schedules, yet are only partially related in their socio-demographic profiles. In other words, the present approach allows the segments of the population to ‘emerge’ from the data. For that, we use latent class cluster analysis. Our empirical contribution to literature is then addressing the question of whether such distinct groups exist, and identifying which groups the travellers can be classified into based on the changes they make to their schedules, their socio-economic attributes, and personal characteristics like motion sickness. Furthermore, our choice to use latent class analysis allows us to reveal these pattern changes rather than hypothesise them, and it also allows us to discover the interactions between different on-board and stationary activities. This relates to the lasting discussion about the role of tele-activities in daily schedules — do they substitute or complement, or modify, or have no effects at all on the corresponding in-person activities? (Pawlak et al., 2019)

The paper is structured as follows. Section 2 provides additional background literature, while Section 3 introduces the data and methods. Following that, we present the results of the analysis in Section 4 with additional interpretations, implications for modelling and study limitations discussed in Section 5. Section 6 concludes the study.

## 2. Literature review

In this section, we present first a review of the literature covering activity scheduling during travel and outside travel. We then look into works that have explored the influence of activities done on-board a vehicle on activities done outside. Finally, based on our review of literature, we introduce the knowledge gap to which we aim to contribute.

### 2.1. On-board activities

Over the years, research has conventionally departed from an assumption that travel time is negatively valued (and thus, should be minimised), in parts because it is “lost time” that cannot be used for other activities (Frei et al., 2015). However, many studies have argued that engaging in activities during travel can reduce the disutility associated with travel (Keseru and Macharis, 2018). The rise of digital resources and ICT has facilitated undertaking multiple activities, also known as multitasking, during travel (Schwanen and Kwan, 2008) and has also sparked the research interest in its effects on the travel experience (as discussed by e.g., Pawlak et al., 2019). One of the possible benefits of multitasking during travel is productive time use, which allows travellers to shift activities from another time to travel and free valuable time for other (or longer) activities outside of travel (stationary activities) (Kröger et al., 2019). Another equally important benefit is the ability to relax during travel (Ettema and Verschuren, 2007; Frei et al., 2015) and possibly save energy for more activities outside of it (Singleton, 2019). With increased productivity, or more enjoyable trips, travel time is seen less as a lost time.

It is unclear what activities would be of interest on board automated vehicles. Various studies have compiled the activities undertaken during travel, focusing on public transport where the traveller does not contribute to the driving (Keseru et al., 2020). Such activities include working, talking, or using ICT, and gazing out the window or relaxing (Lyons et al., 2007; Ettema and Verschuren, 2007; Susilo et al., 2012; Ettema et al., 2012). Engaging in these activities was associated with higher satisfaction and more positive perception of travel time (Lyons et al., 2007; Susilo et al., 2012). Along the same lines, studies have inquired about the activities that travellers expect to perform in automated vehicles. This interest arises from the expectation that new and improved non-driving activities during travel could constitute a large share of the benefits of automated vehicles. Here, early stated preference studies like (Fraedrich et al., 2015) investigated travellers’ multitasking intentions in an automated vehicle and found that most travellers are not interested in making their travel time more productive, but rather they are interested in non-work activities (listening to music, window gazing) that they are already accustomed to doing on-board. In their survey analysis, Wadud and Huda (2019) found evidence for interest in productive use of travel time (work and studying),especially in outbound commute trips, while passive activities were more frequent in return trips to “switch-off”.

### 2.2. Stationary activity planning and replanning

As mentioned in the first section, we expect that on-board activities in automated vehicles can influence stationary activities. In this context, it is relevant to review, first, what we know about planning stationary activity schedules and, second, what we know about how people adjust their plans in response to various interventions.

To start with the first, economists have formally described how people allocate their time. The principle of classical time allocation frameworks is that time is used in a way that maximises its associated utility (Becker, 1965; DeSerpa, 1971). According to the formalisation of Becker (1965), when individuals allocate time to a non-market activity (i.e activities that do not earn them income), they spend the income received through market activities when they consume goods and service, but they also produce utility. Thus, the allocation of time for non-market activities is done with the aim of maximising this utility, subject to constraints of income and prices of goods (Juster, 1990). Later economic models of time allocation have continued building on this fundamental model (DeSerpa, 1971; Gronau, 1973). Time geography literature has further defined the constraints associated with time use, with Hägerstrand (1970) identifying that time use is constrained by limitations in capability, but also by the need for other individuals or tools, and finally by laws and norms. Adding to this formalisation, Cullen and Godson (1975) added the concept of activity flexibility, identifying that certain activities are fixed in time and/or space and cannot be easily moved or modified. These activities are often related to the basic needs of individuals (sleep and eating), or to work/study activities.

The next question to consider is how people replan their activities. The theoretical work of Clark and Doherty (2009) examined, within the framework of time geography, the decision process that individuals go through as they make modifications in their schedules. The modifications reported by respondents include adding or deleting an activity, modifying the start or end time of an activity, or modifying both. The rearrangements were driven by different factors, some related to external factors (interpersonal needs, conflict scheduling issues), and other related to the individual's needs and desires. When considering rescheduling processes, the time planning horizon is important, as Clark and Doherty (2009) identified that adjusting the start time or duration of an activity is an easier modification than adding or omitting an activity, which requires more planning and would happen early in the rescheduling process.

To understand what actual changes can be done on activity schedules, we look now into the empirical evidence in replanning processes. We find the work of Sundo and Fujii (2005) who studied the individuals' response to a 4-day working week, which came along with a 2-hour increase in daily work hours. The participants responded to the two-hour work-time increase by decreasing the duration of household activities before and after work. Activity type was found to be a significant influencing factor in rescheduling, as pre-work activities and sleep were found to be less flexible than others. This was also a finding in van Bladel et al. (2009)'s analysis of activity-travel data from Flanders, Belgium, though other factors like the duration of the activity and the participation of other individuals were significant as well. Furthermore, work activity was rarely rescheduled and often acted as an anchor around which the other activities are scheduled (van Bladel et al., 2009).

While automated vehicles will likely not produce such a large disruption in daily schedules, it is valuable to look at the recent Covid-19 pandemic to observe activity changes in response to changes in external conditions. Changes like extending sleeping hours by delaying bedtime and waking time were noted (Cellini et al., 2020). While there was naturally less travel (Politis et al., 2021), and thus fewer activities outside of the house (Fatmi et al., 2021), the diversity of activities at home increase, largely thanks to digital resources which reduced the location constraints of many activities (Primi and Marchioro, 2020; Fatmi et al., 2021). Of course, not all activities can be performed remotely, a limitation that should be relevant for automated vehicles as well.

### 2.3. The influence of on-board activities on stationary activities

Whereas there is rich literature exploring the on-board activities and stationary activities separately (as reviewed above), the literature on the interaction between both is rather limited. Several notable exceptions, however, are discussed next.

In terms of theoretical development, studies have observed that engaging in activities during travel can have consequences beyond the quality and usefulness of the trip itself, extending to scheduling patterns outside of travel. Pawlak et al. (2017) formalised the joint choice of on-board and neighbouring stationary activities and their attributes (e.g., ICT use) using data from a UK study on productive use of time during travel in trains. Relatedly, Pudāne et al. (2018) and Mokhtarian (2018) discussed and formalised the interaction between on-board activities and time use during the day. They focus on the "saved time effect' - the potential of on-board activities to free up time if activities are transferred to the travel episode from a stationary location (Pudāne et al., 2018; Mokhtarian, 2018). A similar phenomenon was observed with regards to ICT tools, as Schwanen and Kwan (2008) identified that ICT resources provide more spatial flexibility (e.g., the ability to engage in meetings virtually) and support multitasking, thus freeing up time (Schwanen and Kwan, 2008). More generally, ICT tools and telecommunications facilitate flexibility through activity substitution (meaning that an online activity is performed instead of an in-person activity) as well as through more complex processes like complementarity (meaning that engaging in an activity online leads to spending more time on the same activity in person) and modification (Mokhtarian, 1990, 2000; Pawlak et al., 2019).

Interactions between on-board and stationary activities have been observed also within the growing body of empirical studies on automated vehicles. For example, Correia et al. (2019) observed how frequently travellers would transfer their work activity to the travel episode as opposed to just working extra time during travel. Pudāne et al. (2019) qualitatively explored how on-board activities may interact with stationary ones — this interaction may make schedules more "efficient", but it also may increase time pressure. The study of Kim et al. (2020) analysed survey data from Georgia, USA, and identified that time flexibility was a factor of interest, especially for middle-aged high-income individuals who expected more activity changes and more complex re-arrangements as a result of this time flexibility, including activity transfer to the travel episode and usage of the "freed-up" time (Kim et al., 2020). Lastly, Pudāne et al. (2021)'s MDCEV study, from which the survey data will be reused in this study, identified joint changes in stationary and on-board activities in some socio-demographic groups (e.g. more work activities on-board and more time spent on leisure stationary by highly educated individuals). These changes, however, were not large at the group-aggregate level.

### 2.4. Knowledge gaps and contribution of our study

Building on the works reviewed here, we identify a clear knowledge gap. We have observed that much work has been done to understand how people schedule and reschedule their activities, yet not much of it has quantified the changes in activities. Thus, we aim with this research to provide an empirical contribution by quantifying changes in activity schedules. Similarly to Kolpashnikova and Kan (2021) and Bellagarda et al. (2020), we use a clustering method to identify segments of activity rescheduling patterns using self-reported time use data (see Pudāne et al., 2021). Furthermore, as far as we know, no study has addressed unobserved heterogeneity in daily activity-travel schedule changes with autonomous vehicles. Therefore, the approach we take is not to pre-define the clusters and use K-means clustering to classify the sample, but rather we aim to reveal the segments using latent class clustering, a probabilistic clustering method (see Section 3.3). Finally, we contribute to the literature covering the interactions between the different types of activities (on-board and stationary) at an aggregated level. Indeed, we do not address activity changes individually and in isolation, but we rather look at the most common changes within a cluster and try to identify possible links between the different types of activities and understand the decision-making process behind these changes.

## 3. Data and methods

### 3.1. Survey

To assess the potential schedule rearrangements brought by fully automated vehicles, an interactive stated activity-travel survey was designed and conducted by Pudāne et al. (2021).[2] We will be reusing this data in our research to further examine the heterogeneity of potential activity and travel changes.[3] Following is a brief explanation of the data, for a more detailed description, see Pudāne et al. (2021).

The survey is composed of three parts. The first part is an introduction to fully self-driving automated vehicles (level 5 according the SAE classification Society of Automotive Engineers, 2018) and the interactive survey task. In the second and main part, the respondents were asked to report a recent workday schedule with their most commonly used mode of transport. To do so, the respondents could choose from a list of activities and trips (see Fig. 1) with some stationary activities being tied to specific trips (e.g. shopping can only occur in a shop, services only in a service location, night sleep can only take place at home). If none of the proposed activities were appropriate, the respondents had the possibility to choose the activity "Other" and describe what the activity entailed. The process followed is that respondents would select activities and insert them in the schedule, choosing the start time, duration, and order of activities. They could also add the associated trip fragment, but for some location-bound activities, such as work, the trip fragment was automatically inserted in the schedule. Trip durations were also pre-defined, based on the travel time group the respondent selected. Following that, they were asked to re-design it imagining they had access to a fully automated vehicle using the same procedure. In both present and future schedule, respondents could add activities during travel fragments, reflecting activity engagement during travel (this information was shared during the instruction video). Respondents also had the option to copy the current schedule and use it as a base for their new schedule.

In the third and final part of the survey, the respondents were asked about their expectations of automated vehicles (expected usage frequency, whether they would purchase one etc.), their interest in technology, as well as other indicators like sensitivity to motion sickness and time pressure.

### 3.2. Sample

The survey was shared through a survey agency in the Netherlands[4] to workers and students. The respondents could be employed or studying, as long as they were regular commuters to their work or study place and had a commute of at least 10 min. The final sample includes 494 individuals. We do not have figures of workers and students in the Netherlands, so we compare our sample with the general Dutch population (see Table 1). We do observe significant deviations in gender, car ownership and travel mode. Some underrepresented groups include cyclists (which may be related to the exclusion of very short trips) and women. The sample over-represents men, the highly educated and high-income groups, as well as car owners. However, these deviations could be because we do not compare our sample with the target population.[5]

Nonetheless, the objective of this study is not to generalise insights on the Dutch population, as doing so with sample data that is not representative could lead to inappropriate results (Kim and Mokhtarian, 2023). We rather aim to have a large enough sample with enough variation to get insight into the heterogeneity of the expected activity-travel changes in the AV-era. For a detailed description of the sample, see Pudāne et al. (2021).

[2] The survey tool and original dataset can be found in Pudane et al. (2021). The survey is described as interactive because it involves composing schedules on a graphical user interface.

[3] The full dataset we used and analysis files can be found in Debbaghi et al. (2024), https://data.4tu.nl/datasets/141522d5-84a8-4ec7-a362-d01ef2c75b7a

[4] Kantar Media (www.kantar.com)

[5] It can be mentioned that the older population (65+) were not part of the sample, which however was expected given that the population of interest is commuters.

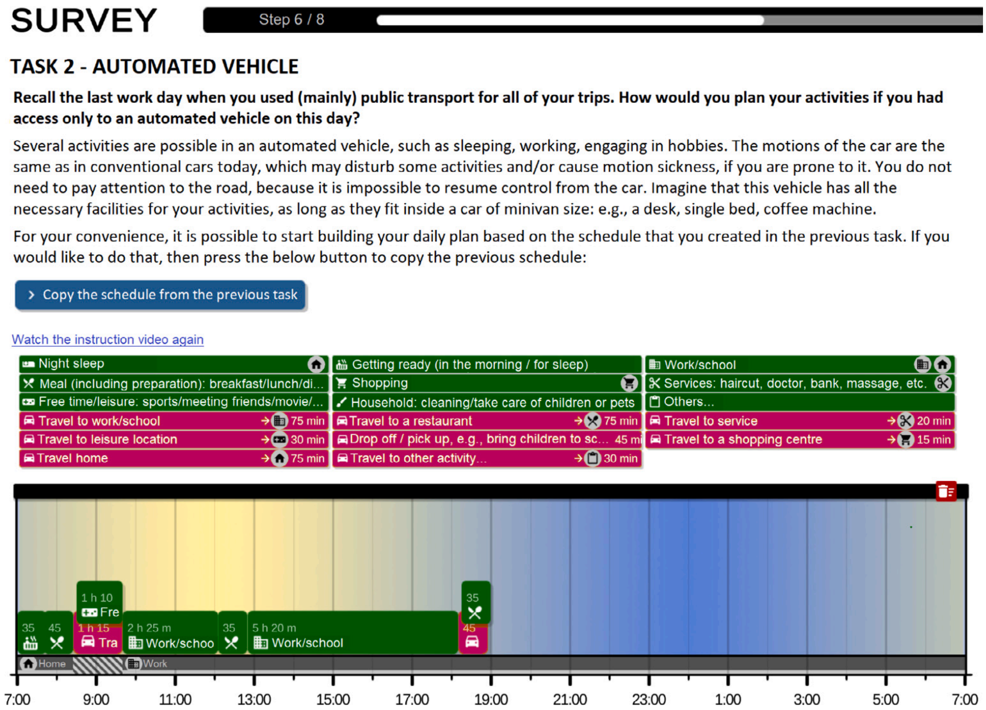


**Fig. 1.** Scheduling of Daily Activities: the Main Interactive Survey Task.

**Table 1**
Socio-demographic characteristics compared to Dutch population.

| Socio-demographic Characteristic | Value | Percentage in sample | Percentage in Dutch population[a] |
|---|---|---|---|
| Gender | Male | 62.75% | 49.62% |
| | Female | 37.25% | 50.38% |
| Age | 18–24 | 8.50% | 9.02% |
| | 25–34 | 21.46% | 13.09% |
| | 35–44 | 20.65% | 12.18% |
| | 45–54 | 30.77% | 13.10% |
| | 55–64 | 18.62% | 13.74% |
| Education[b] | No education/Primary education to MAVO/HAVO and VWO/VMBO | 12.6% | 29.0% |
| | MBO 2, 3, 4 or MBO old structure | 28.74% | 40% |
| | HAVO and VWO/HBO/WO | 8.29% | |
| | HBO, WO Bachelor | 30.16% | 19% |
| | HBO,WO Master, PhD | 20.24% | 11% |
| | Don't know or unknown | 0.00% | 1% |
| Car ownership | Yes | 85.63% | 47.1% |
| | No | 14.37% | 52.9% |
| Travel mode | Passenger cars(driver) | 65.8% (including passenger) | 50% |
| | Passenger cars(passenger) | | 17.90% |
| | Trains | 14.6% (including all public transport) | 6.10% |
| | Bus/tram/metro | | 2.10% |
| | Bicycles | 19.6% | 9.60% |
| | By foot | 0.00% | 4.90% |
| | Others | | 8.70% |

[a] The data on the Dutch population was collected from the CBS online dataset.
[b] We have combined the first three categories of education in our reporting of the sample.

### 3.3. 3-Step latent class models

To examine the changes in activity-travel schedules driven by automated vehicles and reveal traveller clusters, we choose to use a clustering approach, as they have often used to address heterogeneity. In Gálvez-Muñoz et al.'s work on the harmonised European Time-Use Survey (HETUS) data which explored the links between gender and work patterns in different areas in Europe, the clustering is conducted on geographical lines. For most studies that have used clustering methods on time use data, the basis is the activities themselves. Indeed, in Bellagarda et al. (2020), behavioural archetypes are identified based on the activities reported in an Italian time use survey. Kolpashnikova and Kan (2021) is similar in that it identified patterns of daily activities using clustering on the data of the 2006 Japanese Survey on Time Use and Leisure Activities. Self-reported time use surveys are not the only possible data sources, as Timmermans and Van der Waerden (2008) observed travellers on the San Francisco's Bay Area Rapid Transport System in California to record activity engagement during travel, identifying segments of multitasking behaviour using the duration of engagement in the selected activities (Timmermans and Van der Waerden, 2008).

However, deterministic clustering approaches such as those aforementioned have significant biases, thus we look to latent class clustering as an alternative method. Latent class clustering (LCC) assumes that the associations between a set of indicators can be explained with a latent variable (Molin et al., 2016). With this, the population can be classified into homogeneous clusters through probabilistic assignment. That is, LCC identifies underlying sub-classes in a population by estimating the probability of belonging to a class (class membership probability), and the probability of a response conditional to being a member of a class (item-response probability) (Lanza and Collins, 2008). Furthermore, as the goal is also to reach the simplest model with the best fit (parsimony), the number of classes can be evaluated and optimised through different statistical criteria. The respondents will be grouped by their most common characteristics, and conclusions can be inferred from the classes rather then looking at each individual response (Magidson and Vermunt, 2004). In our application, we specifically use the 3-step latent class model, which involves the following steps 1) building a clustering model with only indicators, 2) classifying cases into classes based on posterior class membership probabilities, 3) investigating the association between the classifications and external variables (Vermunt, 2010; Vermunt and Magidson, 2021).

Of the potential indicators to use in our LC model, we select the following: activity duration changes (per type) and commute departure times (outbound and inbound). To further explain the model, we include the different individual characteristics as external variables in the form of covariates in the third step in the aforementioned stepwise approach. Unlike indicators, covariates are not reflections of the latent variable, but are used to explain class membership. Typically, they are variables describing the population demographics, which in our sample would be socio-economic characteristics (age, education, income group etc.) and travel characteristics (transport mode, travel time group, travel frequency), as well as AV-related expectations (expected frequency of usage, intention to purchase etc.), personal characteristics (motion sickness, time pressure, ability to do work in the car). We use the Latent Gold software to produce our model (Magidson and Vermunt, 0000).

### 3.4. Commitment to survey

As will become apparent in our LC analysis, a large share of respondents made no or very small changes in their on-board and stationary activity schedules. We hypothesised that this result may, to some extent, be due to their low commitment to the survey. This link between commitment and schedule changes is possible via two mechanisms. First, respondents who are not sufficiently committed to the survey may be more inclined to keep the status-quo option of no schedule changes, because that requires less effort than changing the schedule (since it was possible to copy the present schedule into the editor of the schedule with AVs; this option was used by roughly 80% of respondents). Second, the respondents may simplify their present schedule by reporting their activities at a low granularity level (e.g., 8 h of work as opposed to 3 work hours, followed by lunch, followed by 4.5 work hours). The consequence of low granularity is less schedule changes because it is not possible to indicate changes in shorter activities that are "aggregated" in the schedule.

If the large share of no-change responses is indeed due to the simplifying attempts of respondents with low commitment to the survey, then these responses should be viewed as less credible. In such case, our LC analysis should come with a disclaimer that the prevalence of schedule changes in response to AVs is underestimated. However, and clearly, we cannot conclude that a certain respondent had low commitment to the survey just because they did not change their schedule or reported large activity blocks.

Literature offers several ways to identify low commitment to survey via indicators, which are suitable for different data types. In attitude or opinion data, presented as a block of Likert-scale questions, it is common to check for 'straightlining' — i.e., selecting the same response for an entire block of rating questions. In stated-choice surveys, it is common to control for lexicographic, non-trading and inconsistent responses (Hess et al., 2010). Sometimes surveys include a control question that should be answered in a certain way by a rational respondent (e.g., a dominated choice). In activity-travel surveys, the analyst may pay attention to responses that do not contain any trips on a given day (Madre et al., 2007; de Haas et al., 2022). de Haas et al. (2022), for example, contrasted the immobility (no trips in a day) with a likelihood that the trip should be made based on individual's employment details (e.g., working full time). In addition, the response times can sometimes be directly used as indicators of respondents' commitment.

For our data, we choose to focus on the response times to non-central survey questions, such as the introduction screen (containing information about the context and structure of the survey) and the video showing how to design the activity schedules. Using these survey parts as an indicator has a potential drawback: we may identify "professional respondents" who skip the introduction and instruction stages, because they are too accustomed to the presented information. However, they may still pay sufficient attention to the core survey questions. While that is a possibility, our analysis still reveals the association between speeding in these initial survey stages and simple responses to the core questions. Because it is unlikely that specifically "professional respondents" would not desire to modify their schedules with AVs, we can conclude that a positive correlation between these variables indicates simplifying efforts in both survey stages. Therefore, we choose to include these measures as covariates, as with the personal socio-demographics, to be added in the third and final step of the 3-step approach. In addition to response times, simplicity of the schedules is also used as a commitment indicator, measured as the number of fragments in the current (non AV) schedule. This indicator also somewhat reflects the granularity and simplicity level in the schedule.

Fig. 2 illustrates the expected latent class model with the indicators, which are the measures of the schedule changes, and the covariates, which represent the attributes and characteristics of the individual respondents. The schedule rearrangements circle represents the latent variable we aim to capture with this model. As mentioned earlier, the 3-step approach entails first estimating the base LC model with the selected indicators, then classifying the responses using the resulting posterior class membership probabilities, and finally relating the resulting classification to covariates of interest. These include what we consider factors related to the perception of AVs (expected AV usage frequency, intention to purchase an AV...), and personal factors like motion sickness and the ability to work in the car. We also include commitment measures like the time spent reading the introduction screen (in seconds), which has 318 words, the time spent watching the instruction video, which shows how to complete the main scheduling task in the survey (in seconds), the number of activity fragments in the initial activity schedule. We also consider whether the respondent chose to copy the current schedule as a basis for designing the schedule with an AV. We point out that in our process of data cleaning and preparation, we also considered these commitment measures and removed 2 outliers with extreme response times in the introduction screen time (5331 s, the next highest is 928 s) and in the instruction video time (72463 s, the next highest is 1224 s). These two respondents likely performed other tasks while having the corresponding survey page open. Hence, this data is not suitable for analysing survey commitment. The result is a sample with 494 responses.

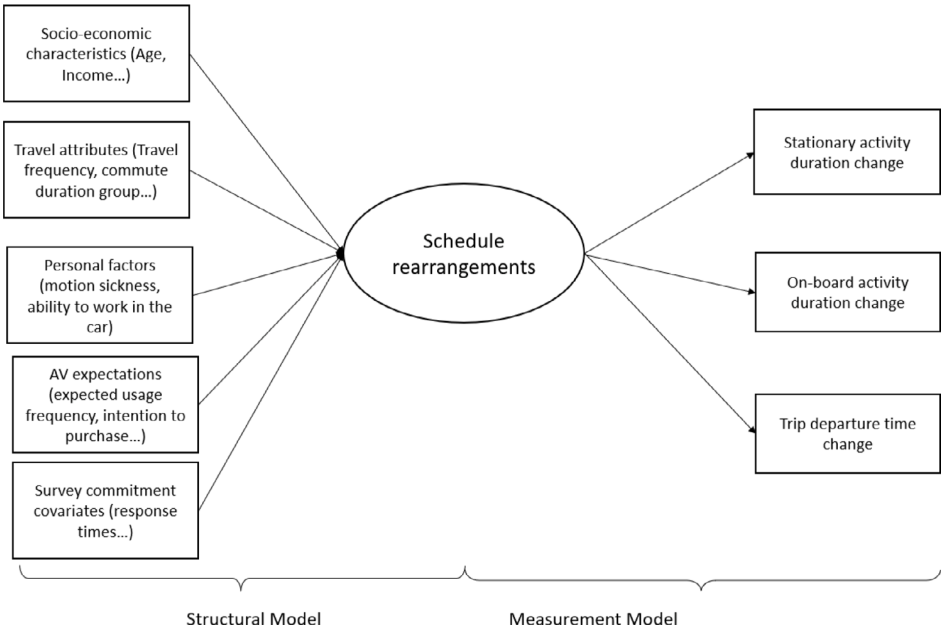


**Fig. 2.** Structure of the Latent Class Model of Schedule Rearrangements and Commitment to Survey.

## 4. Results

### 4.1. Descriptive analysis

The focus of this research is to explore the changes in activity patterns both during travel and outside of it. For that, we begin by looking at the frequencies of the said changes by measuring the instances in which respondents have modified the duration of their activities. Our first observation is that respondents are relatively conservative in reporting modifications, with only 221 out of 494 (45% of the sample) making some change in the duration of their activities, either on-board or stationary. Of these, 142 report change in activities on-board, while 179 report some change in stationary activities. Table 2 below provides a more detailed overview of the frequency of occurrence of changes in activity durations,[6] as well as the respective means and standard deviations. We observe that work, spare time, getting ready and meals are the most widely modified activities. Activities on-board tend to

[6] Activities include night sleep, work/school, getting ready in the morning or for sleep, meals (including preparation), shopping, services like haircut, doctor visit, bank, massage etc., household tasks like cleaning, taking care of children or pets, spare time/leisure like sports, meeting friends, movie etc., and other activities

**Table 2**
Frequencies, Means, and Standard deviations of activity duration increase and decrease by activity type, N=494.

| | | Frequency of increase | Mean of increase (minutes) | SD of increase (minutes) | Frequency of decrease | Mean of decrease (minutes) | SD of decrease (minutes) |
|---|---|---|---|---|---|---|---|
| Sleep | On-board | 8 | 31.88 | 19.99 | 1 | −60.00 | NA |
| | Stationary | 73 | 28.49 | 20.13 | 40 | −27.63 | 30.19 |
| Work/School | On-board | 66 | 62.65 | 35.35 | 7 | −30.00 | 29.16 |
| | Stationary | 48 | 34.27 | 36.80 | 75 | −43.60 | 39.54 |
| Getting ready | On-board | 21 | 24.52 | 16.80 | 3 | −13.33 | 5.77 |
| | Stationary | 38 | 19.47 | 17.39 | 45 | −25.11 | 16.15 |
| Meal | On-board | 41 | 28.66 | 19.37 | 1 | −10.00 | NA |
| | Stationary | 37 | 30.00 | 30.75 | 63 | −28.73 | 23.89 |
| Shopping | On-board | 2 | 20.00 | 7.07 | 1 | −20.00 | NA |
| | Stationary | 4 | 11.25 | 4.79 | 1 | −90.00 | NA |
| Service | On-board | 0 | NA | NA | 0 | NA | NA |
| | Stationary | 2 | 17.50 | 17.68 | 0 | NA | NA |
| Household tasks | On-board | 3 | 35.00 | 21.79 | 0 | NA | NA |
| | Stationary | 22 | 44.09 | 58.26 | 11 | −25.45 | 27.70 |
| Spare time | On-board | 64 | 58.67 | 32.59 | 2 | −22.50 | 24.75 |
| | Stationary | 89 | 50.84 | 44.47 | 39 | −47.18 | 45.43 |
| Other activities | On-board | 4 | 45.00 | 31.09 | 1 | −5.00 | NA |
| | Stationary | 4 | 63.75 | 75.98 | 10 | −72.50 | 61.29 |

increase rather than decrease, which is in line with the expectation that the automated vehicles facilitate on-board activities better than present travel modes. The changes in stationary activities vary (increase or decrease) depending on the type of activities: for example, work activities more often decrease, while spare time more often increases. Taking a deeper look into the magnitude of these changes, we look at the means of the duration changes. Overall, on-board work and spare time increase the most per minute of travel time, followed by on-board meals and getting ready. Meanwhile, stationary work, meals, and getting ready decrease on average, while sleep, household tasks, and spare time increase the most on average. We observe relatively high standard deviations, indicating a high dispersion of the size and direction of activity changes across the sample. This high variance supports the necessity to uncover the unobserved heterogeneity of the schedule changes, which is our main aim.

Turning from activities to the trips, we report first the expected changes in the number of trips. Note again that the durations of the trips were fixed for each respondent. Our data shows that 16 respondents have eliminated trips from their schedules, while only 7 have added at least one trip to their schedules. Both of these are very small shares of the sample size of 494. This indicates that there is, in general, reluctance from respondents to add or eliminate trips from their schedules in response to the availability of AV. Further, we examine the departure time of the commute trips (which are part of all schedules in the processed dataset). We analyse the changes in departure times of the commute trips by taking the difference in departure times between the two schedules.

Looking at the frequencies (see Table 3), we see that 80% (399)of the respondents expect they would not modify their departure times in the workbound trip, while 78% (387) would not change their homebound trip, in line with the conservative expectations with regards to activities. Nonetheless, a non-trivial share of 14% (68) of the sample expect to travel home earlier, while nearly 12% (57) expect to travel to work later. Looking at the magnitude of changes, the work-bound trip is delayed in the AV-schedule compared to the current schedule on average by nearly 30 min, while the homebound trip is advanced to an earlier time by 88 min on average. While the effect is more significant with the home-bound trip, effectively, the average respondent reported a shorter work day in the workplace.

**Table 3**
Frequencies, Means and Standard deviations of commute departure times change (minutes), N=494.

| | Frequency of no change | Frequency of increase | Mean of increase | SD of increase | Frequency of Decrease | Mean of Decrease | SD of decrease |
|---|---|---|---|---|---|---|---|
| Workbound trip | 399 | 57 | 29.39 | 38.30 | 39 | −37.31 | 67.549 |
| Homebound trip | 387 | 40 | 67.00 | 103.68 | 68 | −88.16 | 155.14 |

The activity changes reported in the previous paragraphs are not mutually exclusive. To identify which combinations are most common, Fig. 3 correlates the individual duration changes for every pair of activity categories and trip departure times. The crosses in the figure represent statistically non-significant correlations (p-values lower than 0.05).

The strongest correlation is observed between stationary work and stationary spare time activities (with a negative correlation of −0.48). That is, if someone increases their stationary work duration having an AV, they tend to decrease the time they spend on stationary spare time. The next strongest correlation value (−0.38) is between stationary work and on-board work. The highest positive correlation (0.24) is between stationary spare time and work on-board. The on-board activities have relatively low correlations, while we observe negative correlations between on-board and stationary activities of the same type (work, getting

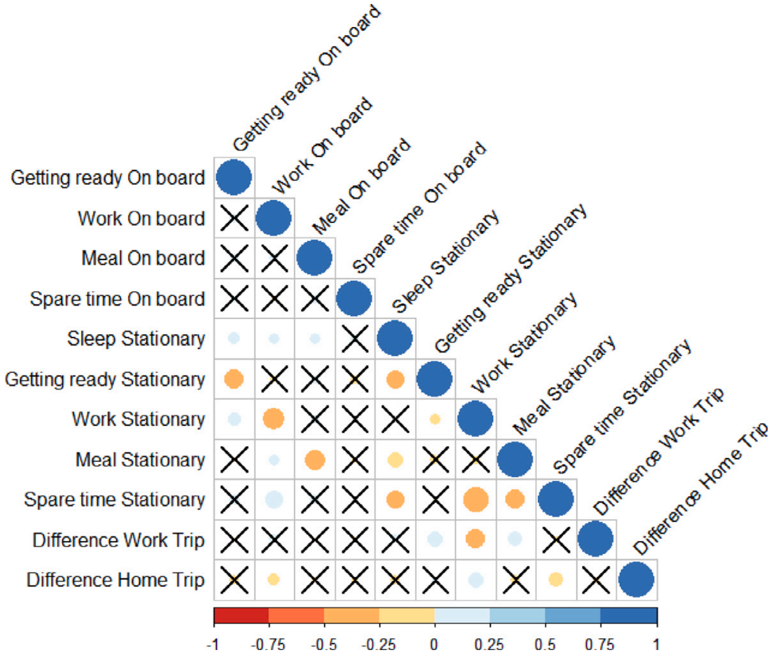


**Fig. 3.** Pearson rank Correlations between On-board Activities, Stationary Activities and Departure Times. The X reflects the non-significant correlations.

ready, meals). That is, when these activities are reduced outside of travel times, they tend to increase on-board. While the opposite could be true as well, the frequency table shows that activities on-board generally increase in the sample, so a transfer of activities from being stationary to the travel episode is likely. Nonetheless, spare time appears to be an exception to this, as the correlation is near 0 and non-significant, indicating no particular link between the change in the stationary and on-board leisure time. As for the travel departure time changes, the most significant is a negative correlation (−0.28) between the difference in work-bound trip departure time and the difference in stationary work duration. That is, if the work-bound trip is delayed, the stationary work duration tends to decrease.

### 4.2. Latent clusters

#### 4.2.1. Model estimation

We cluster schedule changes with AVs using the indicators described in the descriptive analysis: the relative activity duration changes variables for both stationary and on-board activities, as well as travel departure time change. Of these, we omit the indicators for activities that were seldom selected or did not change their duration in the data, namely household tasks, shopping, services, and “other” activities (which were specified by the respondents). Furthermore, sleep on-board is excluded, while keeping the stationary sleep activity, see Table 4.[7]

**Table 4**
Activity and travel change indicators used in the LCC Model.

| On-board activity duration change (minute/minute of travel) | Stationary activity duration change (minute/minute of travel) | Travel departure time change (minute/minute of travel) |
|---|---|---|
| Work activity | Work activity | Homebound trip |
| Spare time activity | Spare time activity | Work-bound trip |
| Meal activity | Meal activity | |
| Getting ready activity | Getting ready activity | |
| | Sleep activity | |

Beginning with the first step of the 3-step approach, we first identify the optimal number of clusters to find the best model. The goals are model fit and parsimony — reaching a model that describes the data well with a minimal number of parameters. To assess the model performance, we use the log-likelihood, the Bayesian information criterion (BIC), as well as the cluster size (no less

[7] Note that ‘Sleep’ was defined as ‘Night sleep’ in the survey, see Fig. 1, which resulted in only few instances of sleep indicated during travel. Activity ’Taking a nap’ was mentioned to respondents as an example of leisure activities.

than 3% of the sample). See Table 5 below for the indicators generated for different latent class cluster models (using Latent Gold software Magidson and Vermunt). The BIC value continues decreasing with every additional cluster; therefore, we should select the model with the largest number of clusters (13 or more) following this criterion. However, such a model is difficult to analyse and interpret also due to the small number of observations in the smallest clusters. We notice that models with more than 5 clusters have classes with less than 3% of the sample belonging to them (which corresponds to less than 15 participants — generally not sufficient to draw substantial conclusions). Therefore, we limit our options for the optimal cluster number to 5 or less. To further decide on the number of classes, we use the Bivariate residuals (BVR), which describe the fit between two indicators. These values assess the extent to which the 2-way association(s) between any pair of indicators are explained by the model (Magidson and Vermunt, 2004). Thus, models with minimal BVR values are preferred, but any BVR value below 3.84 is considered insignificant. Considering the BVR values do not provide a clear-cut preferred option, we go back to the BIC value and select the model with the lowest BIC value. With that, the 5-cluster model is selected for further analysis.

**Table 5**
Model fit with different latent cluster sizes.

| No. of classes | LL | BIC(LL) | Npar | Classification error | Smallest cluster size | Nr of significant BVR |
|---|---|---|---|---|---|---|
| 1-Cluster | −24991.21 | 50 118.88 | 22 | 0.000 | 100% | 34 |
| 2-Cluster | −15281.39 | 30 841.89 | 45 | 0.000 | 38.69% | 45 |
| 3-Cluster | −13439.34 | 27 300.46 | 68 | 0.000 | 18.47% | 44 |
| 4-Cluster | −12105.75 | 24 775.94 | 91 | 0.003 | 10.12% | 50 |
| 5-Cluster | −11313.50 | 23 334.10 | 114 | 0.000 | 5.88% | 48 |
| 6-Cluster | −10728.18 | 22 306.11 | 137 | 0.000 | 3.49% | 53 |

#### 4.2.2. Analysis of the final model

With the optimal number of clusters identified, the model is re-estimated and posterior class membership probabilities are obtained. The result is then cluster profiles reflecting the class assignment of the participants. Each cluster has distinct characteristics based on mean values of the selected indicators. The last step is then to conduct the step-3 analysis by adding the covariates to the classification file. We report the final model with the cluster profiles and covariates in Table 6.

We point out that we do not use absolute activity duration differences in our model, but rather proportions of the duration change to the total travel time calculated at the level of each individual response. Therefore, for example, value 0.4 for on-board work time increase (rounded first value in Cluster 3) means that these respondents would on average increase their on-board work duration by 24 min in a day that has 1 h of travel (e.g., 30-minute commute both directions). We implemented this normalisation in order to address the potential bias of activity duration changes due to travel time, as longer travel times provide more flexibility for introducing on-board activities. Without the normalisation, it could happen that the respondents with short travel times and, consequently, short added on-board activities are classified together with respondents with long travel times and no added on-board activities. The resulting values in the model then represent the change travellers expect to make in specific activities or trip departure time per minute of travel.

Before addressing the cluster profile, we first look at the selection of the covariates. All socio-economic factors (age, education, income...) and travel characteristics (travel time, frequency, mode) were initially included as covariates (see Fig. 2). In an iterative way, we eliminated the non-significant covariates (at a significance level of 5%) and report here the final model with only the remaining significant ones. We find that of the socio-demographics, only gender, education and travel time group significantly explain the clusters. As for the perception of AV factors, the significant ones are expectations of AV usage frequency, intention to own an AV, daily time pressure, and ability to do work in the car. Factors like motion sickness and experience with new technology were not found to significantly explain the classification. Finally, all commitment measures but the time spent on the introduction video were found to be significant.[8] For our evaluation of commitment, we use the introduction video time, which reflects if respondents were speeding through the first stages of the survey. We also use the number of activity fragments, which indicates the extent to which respondents simplified their present schedules. We consider that schedules with fewer activities may have been composed by combining shorter activities, which are then impossible to modify in the future schedule. Both indicators can reflect the level of commitment of respondents and how inclined they were to take the minimum effort option. The full report on the model can be found in the data folder. Clusters were assigned names matching the largest effect (or lack thereof) observed, we analyse each individually below.

**Cluster 1: 'No Change' & 'Low Commitment'**

The largest cluster, representing 55.2% of our sample, is one in which there is little to no change reported in schedules, be it in activity durations or departure times. Indeed, most of the sample would be assigned to this cluster, as they do not report any change in activity duration on-board, that is they often do not engage in activities during travel and report no change in activity duration outside of travel. The schedule remains largely unchanged as well in the commute trip departure times.

[8] The mean values for the instruction video time are: 119.1 s (cluster 1), 113.5 s (cluster 2), 167.7 s (cluster 3), 176.6 s (cluster 4), 149.4 s (cluster 5). While this covariate was not found to be significant ($p$-value of 0.23), the shortest times match the clusters which were identified to be low commitment.

**Table 6**
Cluster profiles.

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 | Sample average |
|---|---|---|---|---|---|---|
| Schedule changes | None | Small stationary | Work in AV | Spare time in AV | Various activities in AV | |
| Commitment to survey | Low | Low | Appropriate | Appropriate | Appropriate | |
| Cluster size | 55.26% | 15.59% | 13.20% | 10.14% | 5.88% | |
| **Duration changes per minute of travel (minute/minute of travel)** | | | | | | |
| Work on board | 0.0000 | 0.0000 | **0.3988** | 0.1920 | 0.0823 | 0.0765 |
| Spare time on board | 0.0000 | 0.0000 | 0.1453 | **0.5062** | **0.1271** | 0.0775 |
| Getting ready on board | 0.0000 | 0.0000 | 0.1340 | 0.0000 | **0.1294** | 0.0108 |
| Meal on board | 0.0000 | 0.0000 | 0.1340 | 0.0000 | **0.1293** | 0.0251 |
| Work stationary | 0.0000 | 0.0683 | **−0.3124** | 0.0053 | −0.0486 | −0.0173 |
| Spare time stationary | 0.0000 | 0.0341 | **0.2268** | 0.0124 | 0.1380 | 0.0418 |
| Sleep stationary | 0.0000 | 0.0407 | 0.1323 | −0.0022 | 0.0354 | 0.0255 |
| Getting ready stationary | 0.0000 | 0.0242 | −0.0151 | 0.0000 | −0.1509 | −0.0052 |
| Meal stationary | 0.0000 | −0.0125 | −0.0464 | 0.0002 | **−0.2250** | −0.0359 |
| **Departure time changes per minute of travel (minute/minute)** | | | | | | |
| Difference work trip | 0.0002 | 0.0319 | 0.0577 | 0.0000 | **−0.1830** | 0.0023 |
| Difference home trip | 0.0000 | −0.0587 | **−0.2545** | 0.0010 | **−0.5620** | −0.0744 |

| **Covariates** | | | | | | **p-value** | **Sample** |
|---|---|---|---|---|---|---|---|
| Gender | | | | | | 0.002** | |
| Man | 66.67% | 64.93% | 58.35% | 52.01% | 48.49% | | 62.75% |
| Woman | 33.33% | 35.07% | 41.65% | 47.99% | 51.51% | | 37.25% |
| Education | | | | | | 0.001** | |
| No education \Primary education to MAVO \HAVO and VWO \VMBO | 16.82% | 13.30% | 1.60% | 5.58% | 6.95% | | 12.55% |
| MBO 2, 3, 4 of MBO old structure[a] | 31.93% | 35.66% | 12.01% | 22.43% | 28.86% | | 28.74% |
| HAVO and VWO \HBO\WO | 9.34% | 8.93% | 4.67% | 7.12% | 7.01% | | 8.30% |
| HBO[b] \WO (University) bachelor | 27.52% | 27.91% | 37.52% | 36.86% | 32.90% | | 30.16% |
| HBO\WO (University) master, or doctoral | 14.38% | 14.20% | 44.20% | 28.00% | 24.27% | | 20.24% |
| Travel time | | | | | | 0.002* | |
| 10–30 min | 59.77% | 49.62% | 26.15% | 35.21% | 41.55% | | 50.20% |
| 30–60 min | 33.58% | 41.06% | 52.22% | 49.55% | 48.24% | | 39.68% |
| >60 min | 6.65% | 9.32% | 21.63% | 15.25% | 10.21% | | 10.12% |
| Expectation of AV usage frequency | | | | | | 0.001** | |
| For (almost) all of my trips | 33.05% | 41.60% | 58.81% | 50.27% | 66.80% | | 41.50% |
| For many of my trips | 14.75% | 16.98% | 15.57% | 16.16% | 15.35% | | 15.38% |
| For some of my trips | 18.48% | 19.57% | 12.85% | 16.74% | 9.48% | | 17.21% |
| For (almost) none of my trips | 19.90% | 9.67% | 9.14% | 11.10% | 6.01% | | 15.18% |
| I don't know | 13.82% | 12.18% | 3.62% | 5.74% | 2.35% | | 10.73% |
| Consider purchasing an AV | | | | | | 0.023* | |
| Yes | 23.13% | 35.65% | 49.90% | 37.18% | 46.08% | | 31.38% |
| Maybe | 37.72% | 40.50% | 33.97% | 37.61% | 37.81% | | 37.65% |
| No | 35.39% | 17.21% | 14.57% | 23.28% | 13.91% | | 27.33% |
| I don't think I will ever buy a car | 3.76% | 6.65% | 1.56% | 1.93% | 2.19% | | 3.64% |
| Daily time pressure | | | | | | 0.022* | |
| Very low time pressure | 3.02% | 3.09% | 0.79% | 2.93% | 1.44% | | 2.63% |
| Low time pressure | 17.36% | 13.03% | 3.34% | 16.03% | 8.30% | | 14.17% |
| Not low, not high time pressure | 51.90% | 51.54% | 32.82% | 46.23% | 45.51% | | 48.38% |
| High time pressure | 25.47% | 31.22% | 53.33% | 31.74% | 40.91% | | 31.58% |
| Very high time pressure | 2.25% | 1.12% | 9.73% | 3.07% | 3.84% | | 3.24% |
| Ability to work in the car | | | | | | 0.037* | |
| Yes, all or almost all of my work tasks | 8.36% | 7.86% | 19.33% | 20.08% | 18.99% | | 11.54% |
| Most of my work tasks | 14.61% | 21.69% | 33.17% | 26.35% | 26.45% | | 20.04% |
| Some of my work tasks | 34.71% | 33.04% | 37.06% | 35.01% | 35.21% | | 34.82% |
| No, none or almost none of my work tasks | 42.32% | 37.40% | 10.44% | 18.55% | 19.35% | | 33.60% |
| Introduction screen time | | | | | | 0.019* | |
| Mean | 37.64 | 44.85 | 53.92 | 45.51 | 74.97 | | 43.89 |
| Activity fragments | | | | | | 0.000** | |
| Mean | 7.31 | 7.30 | 8.11 | 8.32 | 7.96 | | 7.55 |
| Copy current schedule | | | | | | 0.076 | |
| False | 0.37% | 74.07% | 33.70% | 3.94% | 41.71% | | 19.03% |
| True | 99.63% | 25.93% | 66.30% | 96.06% | 58.29% | | 80.97% |

[a] Equivalent to junior college education.

[b] University of applied sciences.

The lack of engagement in any activities on-board can possibly be explained by the short commute duration, as there is then limited time to effectively engage in any activity. In addition, the ability to do work tasks in the car is limited in this cluster, as it has the highest proportion of individuals who cannot perform any work tasks during travel (42.3%). While most members of this group expect they would use an AV for all trips (33%), this share is significantly lower than the sample average (41.5%). Exposure and knowledge about AVs could be limited in this cluster, as they also have the lowest education levels of all clusters, with 16% completing no or elementary condition, or up to the first three years of secondary education (compared to 12.5% in the sample).

Finally, respondents in this group experience medium time pressure, thus there may be no need for them to make use of the time during travel for activities for that reason.

At the same time, there may be also psychological factors, related to the commitment to the survey, which cause the lack of indicated schedule changes. This cluster spent much less time on the introduction text than the other clusters and the sample average. Furthermore, this cluster has significantly simpler schedules than clusters 3–5, as seen by the lower-than-average number of activity fragments. With this low number of activity fragments, it is possible that respondents deliberately simplified their current schedule by reporting more "aggregated" activities, which would then be more difficult to modify in the future schedule. These factors together lead us to classify this cluster as having low commitment to survey, raising the possibility of underestimated schedule changes.

**Cluster 2: 'Small Changes in Stationary Activities' & 'Low Commitment'**

The second group has a share of 15.6% and shows small changes in the stationary activity durations and departure times. This is in the form of very slight increases in stationary work, sleep, getting ready, and spare time, and slight advancement of the homebound trip.

This cluster is comparable with the first in terms of education, as well as commute duration, though slightly longer, with nearly 50% of this cluster having a commute of 10–30 min. The expectations of this cluster with regards to autonomous vehicles are more positive, as most members expect they would use an AV for all trips (41.6%), and many intend to own an AV (35.6%). We do observe significant uncertainty with regards to ownership, as 40% of this cluster are uncertain about owning an AV, and up to 6.6% have no interest in owning a car at all. Similarly to the first cluster, the ability to do work in the car is low, as most members of this cluster cannot do any tasks in the car (37.4%). Furthermore, the amount of time pressure experienced by this cluster does not indicate a significant need to adapt their schedule, as the daily time pressure is mostly average (51.5% experience neither low nor high pressure).

At first sight, it seems quite unclear why this second largest group slightly adjusted their stationary schedules in response to AVs, given that they do not expect engaging in additional on-board activities in AVs. However, seeing that most respondents (74.1%) in this cluster did not copy their current schedule, and that their schedules have the fewest fragments in the sample, it becomes clear that these small duration changes could have resulted from an imperfect recall of their previously created present-day schedules. Thus, these small changes are likely an artefact of their survey completion tactic, and we estimate that this cluster can be classified as having low commitment as well, due to considerably simpler schedules.

**Cluster 3: 'Work in AV' & 'Appropriate Commitment'**

The third largest cluster in our sample, comprising 13.2% of respondents, expects to significantly increase their on-board work activities (0.39 min of on-board work for every minute of travel). With this increase also comes a decrease in stationary work activities (0.31 min for every minute of travel), indicating a transfer of work activities to the vehicle. Additionally, this group increases spare time both inside and outside the vehicle, and, to a lesser extent, they are interested in extending their stationary sleep time. As for the trip departure times, this group reports earlier homebound trips (by 0.25 min for every minute of travel), resulting in a shorter working day, and more time available, mostly before the commute trips.

With respect to the socio-demographic and attitudinal characteristics, this cluster is significantly different from the others. Possibly related to the higher education levels (44.2% have completed master or doctoral university education), more respondents are able to perform work tasks during travel. The effect of the travel time group is consistent with the expectation that longer travel time would support more activities on-board (52.2% of the respondents have a commute time of 30–60 min). In addition, respondents in this cluster experience the highest levels of time pressure - a combined 66% of the respondents of this cluster indicated that they have high or very high time pressure. Thus, the ability and the necessity to work to relieve the time squeeze are likely the main reasons for this group to indicate interest in working in AVs. Not surprisingly, this group's interest in automated vehicle is relatively high, as up 58% expect to use one for all trips, and 50% would consider purchasing one.

Commitment appears to be higher in this cluster, as the respondents in this cluster spent more time (53 s) on the introduction text than the first two clusters and the sample average (43 s). Furthermore, we observe significant complexity in the schedules, as the number of activity fragments in their current schedule is relatively high (8.1 on average compared to a sample average of 7.5). Thus, we classify this cluster as having appropriate commitment level to the survey.

**Cluster 4: 'Spare Time in AV' & 'Appropriate Commitment'**

This cluster, with a share of 10% of the sample, is most interested in having spare time in AVs (increase of 0.50 min for every minute of travel). In addition, the respondents are also interested in working short amounts of time during travel (0.19 min for every minute of travel). Along with this, spare time also slightly increases outside of travel (0.012 min for every minute of travel). The commute departure times here do not change.

Consistent with the observations made in previous clusters, changes in schedules seem to be associated with high education levels (36.8% have obtained a bachelor's degree) and long travel time (49.5% travel for 30–60 min), the latter especially tied with activity engagement on-board. While the ability to do work tasks in the car is relatively high, respondents in this group do not experience the same levels of time pressure as respondents in cluster 3 (the indicated time pressure in cluster 4 is mostly average — similar to the ratings in clusters 1 and 2). It seems that they may have less urgency to work during travel, even if they are able to do so. With that, leisure activities are the most common on-board, though work is present as well. In this cluster, the interest in new technologies and automated vehicles is slightly lower, with more having no interest in purchasing an AV (23.3% of the group).

In terms of commitment, we observe differences with the other clusters, as there are significant changes in the two main activities. This high proportion could be due to the high complexity and granularity of the schedules, as the number of activity fragments is the highest among all clusters (8.3). Such high complexity indicates a relatively considerable level of focus from the respondents on the scheduling task. Furthermore, the average time spent on the introduction step is comparable to the sample average. Considering respondents in this cluster have shown high schedule complexity and medium response time, we classify this cluster as having appropriate commitment level to the survey.

**Cluster 5: ‘Various Activities in AV’ & ‘Appropriate Commitment’**
Finally, the smallest cluster (5.8% of the sample) is one in which all activities increase in duration on-board, with comparable values. Activities like work, getting ready, and meals are increased on-board but decrease outside of travel, indicating a “transfer” of activities to the vehicle. Spare time, however is an exception, increasing both inside and outside the vehicle. The homebound commute trip is advanced significantly (for every minute of travel, the trip is advanced by 0.56 min), as is the work-bound trip (0.18 min for every minute of travel). It seems that respondents in this cluster would depart earlier to work, while possibly transferring some of the morning activities – such as getting ready and having a breakfast – to the vehicle.

Education levels in this cluster are relatively high, with 58% of the cluster having university level education. Unlike in the previous clusters, we do not observe an association between long travel time and scheduling changes, as the commute time is short or medium in this cluster (41.5% and 48.2% respectively). It is possible that respondents in this cluster engage in light and short tasks that are feasible in these durations. It should also be noted that these numbers are based on a small group of respondents (5.88% of the sample, around 29 observations out of 494). The high engagement in activities could also be a result of general interest in AVs, as members of this cluster have the most positive attitudes towards AVs, with 66% expecting to use an AV for all trips, and 46% intending to own one. Furthermore, most members of this cluster experience medium or high time pressure, and the ability to do work activities in the car is average, as most can do some (35.2%) or most (26.4%) tasks.

Looking at the commitment factors, they reflect relatively good commitment from the participants. Indeed, this cluster has the highest average time spent on the first introduction step (74 s). We point out that while long response times were often associated in our survey with good commitment, we cannot claim that they are necessarily indicative of it, at least not solely. That is, long response times could be due to distractions rather than genuine engagement in the survey. Nonetheless, considering that respondents in this cluster composed schedule with more fragments (7.9) than the sample average, it is classified, overall, as having appropriate commitment level to the survey.

## 5. Discussion

### *5.1. Heterogeneous and changing roles of travel time in daily schedules*

Through our analysis of the schedule rearrangements, a few behavioural patterns emerged, highlighting how respondents expected that they would perform different activities during travel in an AV, and that these activities may have different consequences on time use during the entire day. The two largest clusters in our results expect little to no changes in their schedules, suggesting – on first sight – their belief that AVs will not have any major impacts on their daily lives. This is consistent with other studies that used clustering to explore the attitudes to automated vehicles, many having identified groups of AV-sceptics or change avoiders (Nielsen and Haustein, 2018; Kim and Moon, 2022; Du et al., 2022; Potoglou et al., 2020; Rahimi et al., 2020; Lee et al., 2021; Sheela and Mannering, 2020). Similarly to our findings, Nielsen and Haustein (2018) and Rahimi et al. (2020) found that enthusiasm for AVs was associated with higher education levels, while other studies highlighted that safety concerns were significant drivers of scepticism (Bansal and Kockelman, 2017; Haboucha et al., 2017; Shin et al., 2019). The consideration of latent constructs in investigating the impacts of AVs on activity-travel behaviour was observed in several studies, like Kim and Moon (2022) and Dannemiller et al. (2021). Both studies also identified significant heterogeneity in attitudes to AVs and expected changes in activity-travel behaviour. Further heterogeneity in preferences for automation was also identified by Potoglou et al. (2020), with cross country comparisons, as well as in Lee et al. (2021), which found limited interest in AVs for short distance trips. On a closer inspection to our results, however, we found that these clusters seemed to also be less committed to the experiment — as seen by them rushing through the introduction and instruction screens and indicating fewer activities in their current schedules. Looking at the previously mentioned studies, most did not consider it (Nielsen and Haustein, 2018; Kim and Moon, 2022), or they eliminated responses that would be considered non-committal based on the time spent completing the survey (Potoglou et al., 2020). Du et al. (2022) considered low commitment to some extent by allowing respondents to choose both “Neutral” and “I don’t know” as responses to misconceptions of AVs in their survey. As a result, a cluster of indifferent attitudes emerged, significantly different from the cluster of neutral views.

As commitment was higher, the remaining three clusters saw more prominent expected schedule changes. We can hypothesise the reasons behind these expectations, as well as assign these reasons to possible individual times styles (Cotte and Ratneshwar, 2001; Cotte et al., 2004). For two of the clusters (no. 3 and 5), we observed specific tasks that were conducted in the vehicle, presumably with the purpose of allowing rearrangements in the schedules. The most common activity that fits this mould is work, so we can speculate that AVs provide utilitarian benefits, not dissimilar to those defined for Web services by Cotte et al. (2006). Individuals who expect to conduct work, getting ready and eating on board seem to get these activities checked off and optimise their schedule. What these activities have in common is that they often have high priority in the schedule and are typically fixed in time. As individuals transfer these activities to the newly available travel periods, they make changes accordingly, such as advancing and delaying their commute departure times to spend less time in the workplace. When linking this with the concept of time styles, this behaviour can be matched with the analytic planning orientation, which characterises people who plan extensively and schedule their day ahead of time considering every minute of the day (Cotte and Ratneshwar, 2001; Cotte et al., 2004). Travellers who reported working on board most often used freed-up time for spare-time activities, indicating possibly the need to engineer their high-priority activities to allow for more rest or leisure. It is noteworthy that respondents in these two clusters had the highest reported time-pressure. Possibly, these busy individuals also experience explicit or implicit social pressure to work during travel (Pudāne et al., 2019). For these travellers, the ability to use ICT tools in a private enclosed space is likely an attractive feature of AVs.

For one of the clusters with changes in on-board activities (no. 4), the on-board are less connected with travel behaviour changes, and seem to be rather directly added to the schedule. The main activity here is leisure, and it is not necessarily connected with "time saving" behaviour, but rather with what could be called "time spending" behaviour. For these travellers, the commute trip may be the only time available to unwind and relax and have time to themselves (this is especially the case for individuals with children) or to have "time-out" as was described in Jain and Lyons (2008). This could match the spontaneous planning orientation dimension described by Cotte et al. (2004), which describes individuals who do not necessarily plan their day ahead and are more likely to engage in an activity for the value of that activity itself in that moment, rather than for potential benefits later. Here, the value of the automated vehicles on the schedules is not necessarily in freeing up time to satisfy the need for leisure through a sequence of activity and travel changes, but rather in directly satisfying this need that could not be supported in the original schedules. For travellers that engage in leisure activities during travel, privacy and the level of comfort in the vehicle may be the most attractive features of an AV, allowing them the space and freedom to relax that they may not have outside the travel episodes.

In summary, and perhaps unsurprisingly, our findings highlight considerable heterogeneity in the expectations of automated vehicles, influenced not only by personal characteristics, but also by the commitment to the survey. Some are more interested in its time saving benefits, while others expect to make use of it for leisure and the pleasure of the travel experience. The expected changes in the schedules reflect what travellers consider important, be it work, family time etc, and which activities cannot be satisfied in the time available to them now.

### 5.2. Implications for travel behaviour modelling

A debatable finding of this study is whether travellers are generally conservative in expecting travel behaviour changes as a result of gaining access to automated vehicles. While the two largest clusters in our study align with other literature (Nielsen and Haustein, 2018; Kim and Moon, 2022; Du et al., 2022), we discovered a remarkable relationship between the reported conservativeness and low commitment to the survey by these respondents. Therefore, we cautiously conclude that the extent and complexity of daily schedule changes is likely underestimated in this and other studies. This leads to two-fold implications for travel behaviour modelling.

First, travel behaviour surveys, as in fact all surveys, should control for and mitigate low commitment of the respondents. For example, our survey tool, in addition to the instruction video, showed an example of a schedule to all respondents for 5 s, before they could start designing their schedules (see the survey tool in Pudane et al., 2021). In addition, surveys aiming to gather complex information such as hypothetical schedules, could have more built-in information checks. For example, a respondent may be notified or requested to indicate their activities at a finer level of detail whenever an activity (other than sleep) of more than 4 h is reported. Alternatively, and perhaps ideally, present time use data is often collected in real time, as mobile apps track individuals' movements throughout the day. A way to collect expected future time-use data could be to couple that survey with real-time trials of AVs (such as the chauffeur experiment by Harb et al., 2018), although the typically short durations of such trials do not allow for formation of habits and may be affected by pent-up demand. That is, induced demand may result from participants using the convenient short-term access to an AV to make optional trips that they have been putting off over a longer time period.

Second, our models indicate that automated vehicles will have notable influence on travel (and particularly, commute) departure times. However, we did not observe any increase in the number of trips. This finding is particularly important for travel behaviour modelling for the automated vehicle era. As explained earlier, a prevalent approach in this research area is to represent potential behaviour changes as a result of a reduction in the so-called travel time penalty. It is argued that on-board activities reduce the inconvenience of travel, which will activate latent demand for travel, resulting in more person-trips. Our results contradict this reasoning. Although we observed a non-trivial share of added on-board activities, these did not result in travellers expecting more travel (as we found that only 7 out of the 494 respondents added trips to their schedules). Instead, they resulted in lower-level travel behaviour changes - i.e., changes in departure times and stationary activity durations. This finding thus support the ongoing development of more advanced travel behaviour models that allow for such more varied changes and do not impose increasing person-kilometres (e.g., Yu et al., 2022; Pudane, 2020).

In conclusion, we argue that AVs will likely cause intricate and complex changes in daily activity schedules, and using an assumed reduction of the travel time penalty as a tool to predict those changes is not sufficient and can even provide misleading results. We recommend that modelling approaches consider more possible responses to added on-board activities (such as changes in departure times) and allow for individual differences in those responses. Adopting such models would also allow to more accurately depict not only the total changes in travel demand due to introduction of AVs, but also usage variations.

### 5.3. Limitations

This research is subject to limitations at the level of the survey data and methods. As the survey data includes only commuters and working days, our findings do not encompass the full range of possible travel changes, such as increase in long distance trips. In addition, the travel time to locations is fixed in a survey — thereby, it is not possible for respondents to select a further activity location as a response to AV availability. Such more diverse schedule changes are well captured by the qualitative statement approach adopted by Kim et al. (2020). Clearly, as a natural limitation to the self-reported schedules, there may be errors and inaccuracies in respondents' recall of their days. Other responses, like time pressure, are subject to the interpretation of the respondents. By using these variables as bases for comparisons, there was an inherent assumption that all respondents evaluate them similarly, which may not be completely true. Another limitation related to survey design is the formulation of some questions. For instance, the question "Imagine that you have access to an AV in addition to your current transport modes. Do you think you would overall travel further or more often?" somewhat confuses the difference between travelling further and more often. With this, it is not possible to analyse the expectations of each separately as we do not know if respondents mean to answer for one or the other, or both. This then limits our interpretation of the results. Finally, a limitation of the data we must acknowledge is concerning the response time metrics used to evaluate survey commitment. While we often found long response times to be associated with good commitment, we recognise that they may be imperfect metrics as long response times could be a consequence of distractions or doing another task rather than real commitment.

A further limitation of our study (discussed in 3.2) is that our sample is not fully representative of the Dutch population. We note that women, cyclists, individuals who do not have university level education, and people who do not own a car are under-represented in our sample. We report that age, car ownership, and travel mode are not significant in our model, and thus have little influence on the cluster definition and sizes. Education is more significant to the model, and the resulting profiles show that higher education levels are associated with more changes in the activity-travel schedules (in line with Pudāne et al., 2021). Therefore, it is possible that having overrepresented the highly educated individuals has led us to somewhat over-estimate the size of cluster 3 with work-related activity-travel changes. Note however, also the countering (and possibly stronger) under-estimation of schedule changes captured as the first two clusters with low commitment levels to survey, as discussed earlier. A further consequence of the underrepresentation of some population groups is that we may have missed some new clusters that are specific to this group (Kim and Mokhtarian, 2023). Therefore, the sample representativeness remains a limitation of the data, and subsequently of our results and analysis.

It is important to note that our data reflect expectations of our respondents regarding future schedule changes, which may not correspond to their future actions. This phenomenon, also known as intention-action gap, was observed in an experiment of a 30-hour workweek, in which participants' wishes of how they would use their time were not fulfilled mainly due to constraints that were not considered like the dependency on other schedules (Mullens and Glorieux, 2022). Thinking about this in the context of our research, it may be that activity changes are overestimated because they require coordination with other people (one cannot leave work early if they have meetings requiring their presence). While we focused in our analysis on the potential occurrence of under-estimation of changes, it could also be that changes are overestimated due to over-optimism from respondents. Respondents may also over- or underestimate their ability to change the time or location of various activities. In Mullens et al. (2021), the participants increased the time spent on leisure, but not as much as they had anticipated: "reality did not entirely meet the expectations" (Mullens et al., 2021, p. 18), since the schedules had to be coordinated with other people. The expectations then shifted, and the workers focused more on small increments in existing activities that they could do individually and enjoyed the reduction in time pressure. At the same time, our data may also underestimate the schedule changes in the automated vehicle era, for three reasons. First, if asked few decades ago, many would have underestimated the fundamental daily schedule changes that were brought by spread of mobile and smartphone technologies (Thulin and Vilhelmson, 2007). Second, just as a substantial share of our respondents did not report any changes in their daily schedules, there may be another notable group who may have under-reported their schedule changes, while otherwise completing the survey conscientiously. Third, Singleton (2019) highlighted the importance of reduced stress during travel with AVs, which could be an alternative source of schedule changes. However, it is more difficult, if not impossible, to convey in a survey setting the extent of hypothetically reduced stress levels. Our survey did not attempt to emphasise this change in travel experience.

The above discussion is related to the concept of hypothetical bias that would clearly affect our data (as well as AV studies in general) and could have led to over or under-estimation of schedule changes. Hypothetical bias, which can be defined in the context of our research as "the distance between what people say they would do and what they actually do" (Asensio and Delmas, 2015), have been observed in transport economics studies (Haghani et al., 2021a). For our research, we believe that the lack of familiarity and experience with automated vehicles could be a source of hypothetical bias. This could have lead the participants to be conservative in their estimations of activity-travel schedules. However, as fully automated vehicles are not available, it is difficult to validate this expectation by comparing our results with "revealed" data, or conducting an experimentation as suggested in Haghani et al. (2021b). This is also relevant when thinking about potential over-estimations of the schedule changes in the survey. Indeed, while we consider clusters with low levels of commitment to have potentially under-estimated the changes in their schedules, it is possible that other clusters that have reported changes were too optimistic and overestimated them. This could be to provide more desirable or satisfactory responses to the researcher, an instance of social desirability or conformity bias. Altogether, it is an interesting question whether the schedule changes are over- or under-represented as a result of various biases.

## 6. Conclusions

This paper used a 3-step latent class analysis approach to identify groups of travellers by their expectations of activity and travel changes with AVs. Using travel and activity change indicators (commute departure time and on-board and stationary activity duration changes) on data stemming from an interactive stated activity-travel survey (Pudāne et al., 2021), we identified five main clusters of change-behaviour: *No change, small changes in stationary activities, work in AV, spare-time in AV, and various activities in AV*. Crucially, while the majority of our sample fits in the first two clusters expecting no major changes in their schedules, our analysis revealed that these responses may (partially) be due to low commitment levels to the survey of the respondents. Namely, the lack of expected schedule changes is strongly related to short response times in non-central survey questions and simplified representation of the initial activity schedules. Therefore, we conclude that while aggregate analysis tend to show limited changes in stationary activity schedules with AVs (as in Pudāne et al., 2021), this finding is likely an underestimation due to concealed latent heterogeneity and varied levels of commitment to survey by respondents.

In the clusters where changes were expected (clusters 3–5), changes in on-board activities were intuitively related to changes in stationary activities. One type of combination found in the data was the transfer of work activities to the travel episode. That is, participants would allocate more time in the vehicle for said activity, but less for it outside travel. Other activities like meals and getting ready were often also transferred, though to a lesser extent. A different pattern was observed with spare-time, which increased substantially in the vehicle as well as out of it in some clusters. This could be interpreted as a need for leisure time that is not satisfied in the current schedules. The on-board environment in AVs lets the travellers fulfil this need by relaxing or engaging in other leisure activities.

Beyond the changes in activity durations, intuitive associations were observed with the departure times. Advancing the homebound trip was often associated with an increase in work activities on-board and a decrease outside travel - i.e., a transfer of late afternoon work tasks from the workplace to the car. Along with this, we observe an increase in spare-time activities, which tend to be post-work activities. In other words, we observe intuitive dependencies between the different activities and the travel decisions.

### *6.1. Recommendations for future research*

Our research only represents travellers' expectations at a point in time during the continuous development and deployment of the automated vehicle technology. As technological progress continues, knowledge, exposure and acceptance will likely change as well. To capture these developments, we recommend future research to address and evaluate how the expected activity-travel impacts evolve over time, especially once the technology becomes more widely available. In the meantime, chauffeur experiments that simulate the experience of having an automated vehicles, similar to that in Harb et al. (2018), can provide additional insights on travel behaviour without relying on self-reporting, which is subject to various biases. Furthermore, it is important to point out that the survey asked travellers to report a regular working day retroactively, that is, as they remember it. In time-use research, recording diaries of multiple days for a specific period of time is a more accurate depiction of the activity schedules. Complementing future experiments of automated vehicles or chauffeur experiments with time-use diaries would allow a more insightful view on the potential realities of activity scheduling in an AV future.

Finally, it is noteworthy that schedule changes in our survey occurred even without an increase in daily travel time, which has been often postulated in simulations (e.g. Childress et al., 2015) and empirical literature (e.g. Kim et al., 2020). This, together with our uncovered heterogeneity in schedule changes, puts to question the validity of travel time penalty approaches for modelling travel behaviour with AVs, which postulate that the only or primary impact of AVs is the reduction of inconvenience associated with travel time. While travel time penalties have served well as a convenient tool to model travel behaviour with existing transport modes, we believe that they fall short in capturing the potential activity-travel changes resulting from the introduction of automated vehicles. Indeed, as this technology promises to revolutionise how time is used in travel, it seems to also more substantially affect the time-use outside of travel. This poses significant challenges for future travel behaviour modelling with automated vehicles.

## CRediT authorship contribution statement

**Fatima-Zahra Debbaghi:** Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Maarten Kroesen:** Conceptualization, Supervision, Writing – review & editing, Data curation, Methodology, Writing – original draft. **Gerdien de Vries:** Supervision, Writing – original draft. **Baiba Pudāne:** Conceptualization, Data curation, Supervision, Writing – review & editing, Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data available at: https://data.4tu.nl/datasets/141522d5-84a8-4ec7-a362-d01ef2c75b7a.

## Acknowledgements

The authors would like to acknowledge Prof. Caspar Chorus (Delft University of Technology) for his supervision and support. The authors would also like to thank Francisca Mullens (Department of Sociology, Vrije Universiteit Brussel) for her valuable feedback and insightful discussions. We would also like to acknowledge the three anonymous reviewers who reviewed our manuscript and provided constructive feedback which helped us improve our work. All authors have read and agreed to the published version of the manuscript.

## Appendix

This appendix contains an overview of the survey questions and answer key (see Tables A.1–A.3).

**Table A.1**
Socio-economic attributes.

| Question | Answer | Key |
|---|---|---|
| *What is your gender?* | 1 | Man |
| | 2 | Woman |
| *What is your age group?* | 1 | 18–24 |
| | 2 | 25–34 |
| | 3 | 35–44 |
| | 4 | 45–54 |
| | 5 | 55–64 |
| | 6 | 65–74 |
| | 7 | 75+ |
| *What is the highest education level you completed?* | 1 | No education/Elementary education |
| | 2 | LBO/VBO/VMBO/MBO 1 |
| | 3 | MAVO/First 3 years of HAVO and VWO/VMBO |
| | 4 | MBO 2, 3, 4 of MBO (Old structure) |
| | 5 | HAVO and VWO (Bovenbouw)/HBO-/WO-Foundation |
| | 6 | HBO/WO Bachelor |
| | 7 | HBO/WO Master or Doctoral |
| | 8 | Do not know/Do not want to tell |
| *What is the size of your family?* | 0–8 | Number of family members |
| *How many children are in your household?* | 0 | No children |
| | 1 | One child |
| | 2 | Two children |
| | 3 | 3 children or more |
| *What is your family cycle?* | 1 | Single; up to and including 34 y.o |
| | 2 | Single; 35–39 y.o. |
| | 3 | Single; 40–49 y.o. |
| | 4 | Singe; 50–64 y.o. |
| | 5 | Single; 65+ y.o. |
| | 6 | Adult household; main breadwinner up to and including 34 y.o. |
| | 7 | Adult household; main breadwinner 35–39 y.o. |
| | 8 | Adult household; main breadwinner 40–49 y.o. |
| | 9 | Adult household; main breadwinner 50–64 y.o. |
| | 10 | Adult household; main breadwinner 65+ y.o. |
| | 11 | Household with children; youngest up to and including 12 y.o. |
| | 12 | Household with children; youngest 13–17 y.o. |
| *What is your income range?* | 1 | Minimum (<€ 14.100 Euro) |
| | 2 | Below average (€ 14.100–<€ 29.500) |
| | 3 | Average (€ 29.500–<€ 43.500), including negative income |
| | 5 | 1-2x Average (€ 43.500–<€ 73.000) |
| | 6 | 2x Average (€ 73.000–<€ 87.100) |
| | 7 | More than 2x average (>= € 87.100) |
| | 9 | Do not know \do not want to tell |
| *What is your work type?* | 1 | Entrepreneur |
| | 2 | Employed |
| | 3 | Employed by government |
| | 4 | Not fit for work |
| | 5 | Unemployed \job-searching \assistant |
| | 6 | Retired |
| | 7 | Student \pupil (15+) |
| | 8 | Housewife \househusband \other (incl. <15 y.o.) |
| | 9 | Do not know \do not want to tell |

**Table A.2**
Travel preferences.

| Question | Answer | Key |
|---|---|---|
| *How many days per week do you travel to work?* | 0 | 4 or more days a week |
| | 1 | 1–3 days a week |
| | 2 | (Almost) never, I work from home |
| *What is your main transport mode on a normal working day?* | 0 | Car (as driver) |
| | 1 | Car (as passenger) |
| | 2 | Public transport |
| | 3 | Bicycle |
| | 4 | Walk |
| *How long does a single trip take to your work/study location (door to door)?* | 0 | <10 min |
| | 1 | 1030 min |
| | 2 | 3–60 min |
| | 3 | >60 min |
| *Think of the last work day where you (primarily) used *travelMode* for all your trips. Which day of the week was that?* | 0 | Monday |
| | 1 | Tuesday |
| | 2 | Wednesday |
| | 3 | Thursday |
| | 4 | Friday |
| | 5 | Saturday |
| | 6 | Sunday |
| *What time did you wake up on that day?* | | |

**Table A.3**
AV-related questions.

| Question | Answer | Key |
|---|---|---|
| *Do you own a car?* | 0 | Yes |
| | 1 | No |
| *How long do you travel daily on average? (Trips to all activities, including walking time.)* | | Time |
| *Imagine that you have access to an AV in addition to your current transport modes. Do you think you would overall travel further or more often?* | 0 | Yes, I would travel further away or more often |
| | 1 | No, I would travel just as far and often as I do now |
| | 2 | No, I would travel nearer or less often |
| | 3 | I don't know |
| *If you had access to an AV, how often would you use it for your daily trips, if the travel costs were comparable with your current travel costs?* | 0 | For (almost) all of my trips |
| | 1 | For many of my trips |
| | 2 | For some of my trips |
| | 3 | For (almost) none of my trips |
| | 4 | I don't know |
| *Do you suffer from motion sickness during travel? (When you make use of a car, bus, train, bicycle, plane or a boat)* | 0 | Yes, almost or almost always |
| | 1 | Yes, often |
| | 2 | Yes, sometimes |
| | 3 | No, never or almost never |
| *Motion sickness explanation* | | Open-ended answer |
| *Do you often try out new technology before your friends and neighbors?* | 0 | Often or very often |
| | 1 | Sometimes |
| | 2 | Seldom or (almost) never |
| *Have you heard of automated vehicles prior to this survey?* | 0 | Yes |
| | 1 | Maybe |
| | 2 | No |
| *If you need a new car, would you then consider obtaining an AV, in case it costs just as much as a normal car and you do not need driving license?* | 0 | Yes |
| | 1 | Maybe |
| | 2 | No |
| | 3 | I don't think I will ever buy a car |
| *Considering AV Explanation* | | Open ended answer |
| *Assess the daily time pressure that you experience — do you have a feeling that you have too little time for all the things that you must do in a day?* | 0 | Very low time pressure |
| | 1 | Low time pressure |
| | 2 | Not low, not high time pressure |
| | 3 | High time pressure |
| | 4 | Very high time pressure |
| *If you had two extra hours per day, what would you use them for?* | | Open ended answer |
| *Could you perform your work tasks in a comfortable car where you do not get motion sick and have internet connection?* | 0 | Yes, all or almost all of my work tasks |
| | 1 | Most of my work tasks |
| | 2 | Some of my work tasks |
| | 3 | No, none or almost none of my work tasks |

## References


Anderson, J.M., Kalra, N., Stanley, K.D., Sorensen, P., Samaras, C., Oluwatola, O.A., 2014. Introduction. In: Autonomous Vehicle Technology. In: A Guide for Policymakers, RAND Corporation, pp. 1–8, URL www.jstor.org/stable/10.7249/j.ctt5hhwgz.8.

Asensio, O.I., Delmas, M.A., 2015. Nonprice incentives and energy conservation. Proc. Natl. Acad. Sci. 112 (6), http://dx.doi.org/10.1073/pnas.1401880112, URL https://pnas.org/doi/full/10.1073/pnas.1401880112.

Auld, J., Sokolov, V., Stephens, T.S., 2017. Analysis of the effects of connected–automated vehicle technologies on travel demand. Transp. Res. Rec.: J. Transp. Res. Board 2625 (1), 1–8. http://dx.doi.org/10.3141/2625-01, URL http://journals.sagepub.com/doi/10.3141/2625-01.

Bansal, P., Kockelman, K.M., 2017. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transp. Res. Part A: Policy Pract. 95, 49–63. http://dx.doi.org/10.1016/j.tra.2016.10.013, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856415300628.

Becker, G.S., 1965. A theory of the allocation of time. Econ. J. 75 (299), 493–517. http://dx.doi.org/10.2307/2228949, URL https://academic.oup.com/ej/article/75/299/493-517/5250146.

Bellagarda, A., Patti, E., Macii, E., Bottaccioli, L., 2020. Human daily activity behavioural clustering from time use survey. In: 2020 AEIT International Conference of Electrical and Electronic Technologies for Automotive. (AEIT AUTOMOTIVE), pp. 1–6. http://dx.doi.org/10.23919/AEITAUTOMOTIVE50086.2020.9307408.

Cellini, N., Canale, N., Mioni, G., Costa, S., 2020. Changes in sleep pattern, sense of time and digital media use during COVID-19 lockdown in Italy. J. Sleep Res. 29 (4), http://dx.doi.org/10.1111/jsr.13074, URL https://onlinelibrary.wiley.com/doi/10.1111/jsr.13074.

Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an activity-based model to explore the potential impacts of automated vehicles. Transp. Res. Rec.: J. Transp. Res. Board 2493 (1), 99–106. http://dx.doi.org/10.3141/2493-11, URL http://journals.sagepub.com/doi/10.3141/2493-11.

Clark, A.F., Doherty, S.T., 2009. Activity rescheduling strategies and decision processes in day-to-day life. Transp. Res. Rec.: J. Transp. Res. Board 2134 (1), 143–152. http://dx.doi.org/10.3141/2134-17, URL http://journals.sagepub.com/doi/10.3141/2134-17.

Correia, G.H.d., Looff, E., van Cranenburgh, S., Snelder, M., van Arem, B., 2019. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transp. Res. Part A: Policy Pract. 119, 359–382. http://dx.doi.org/10.1016/j.tra.2018.11.016, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856417311461.

Cotte, J., Chowdhury, T.G., Ratneshwar, S., Ricci, L.M., 2006. Pleasure or utility? Time planning style and web usage behaviors. J. Interact. Market. 20 (1), 45–57. http://dx.doi.org/10.1002/dir.20055, URL https://linkinghub.elsevier.com/retrieve/pii/S1094996806700445.

Cotte, J., Ratneshwar, S., 2001. Timestyle and leisure decisions. J. Leis. Res. 33 (4), 396–409. http://dx.doi.org/10.1080/00222216.2001.11949951, URL https://www.tandfonline.com/doi/full/10.1080/00222216.2001.11949951.

Cotte, J., Ratneshwar, S., Mick, D.G., 2004. The times of their lives: Phenomenological and metaphorical characteristics of consumer timestyles. J. Consum. Res. 31 (2), 333–345. http://dx.doi.org/10.1086/422112, URL https://academic.oup.com/jcr/article-lookup/doi/10.1086/422112.

Cullen, I., Godson, V., 1975. Urban networks: The structure of activity patterns. Prog. Plan. 4, 1–96. http://dx.doi.org/10.1016/0305-9006(75)90006-9, URL https://linkinghub.elsevier.com/retrieve/pii/0305900675900069.

Dannemiller, K.A., Mondal, A., Asmussen, K.E., Bhat, C.R., 2021. Investigating autonomous vehicle impacts on individual activity-travel behavior. Transp. Res. Part A: Policy Pract. 148, 402–422. http://dx.doi.org/10.1016/j.tra.2021.04.006, URL https://linkinghub.elsevier.com/retrieve/pii/S096585642100104X.

de Haas, M., Kroesen, M., Chorus, C.G., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2022. Didn't travel or just being lazy? An empirical study of soft-refusal in mobility diaries.

Debbaghi, F.Z., Kroesen, M., De Vries, G., Pudane, B., 2024. Daily schedule changes in the automated vehicle era: Uncovering the heterogeneity behind the veil of low survey commitment. Supporting data and software. Version 3. http://dx.doi.org/10.4121/141522d5-84a8-4ec7-a362-d01ef2c75b7a, URL https://data.4tu.nl/datasets/141522d5-84a8-4ec7-a362-d01ef2c75b7a.

DeSerpa, A.C., 1971. A theory of the economics of time. Econ. J. 81 (324), 828–846. http://dx.doi.org/10.2307/2230320, URL https://academic.oup.com/ej/article/81/324/828-846/5234082.

Du, M., Zhang, T., Liu, J., Xu, Z., Liu, P., 2022. Rumors in the air? Exploring public misconceptions about automated vehicles. Transp. Res. Part A: Policy Pract. 156, 237–252. http://dx.doi.org/10.1016/j.tra.2022.01.003, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856422000039.

Ettema, D., Friman, M., Gärling, T., Olsson, L.E., Fujii, S., 2012. How in-vehicle activities affect work commuters' satisfaction with public transport. J. Transp. Geogr. 24, 215–222. http://dx.doi.org/10.1016/j.jtrangeo.2012.02.007, URL https://linkinghub.elsevier.com/retrieve/pii/S0966692312000567.

Ettema, D., Verschuren, L., 2007. Multitasking and value of travel time savings. Transp. Res. Rec.: J. Transp. Res. Board 2010 (1), 19–25. http://dx.doi.org/10.3141/2010-03, URL http://journals.sagepub.com/doi/10.3141/2010-03.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp. Res. C 40, 1–13. http://dx.doi.org/10.1016/j.trc.2013.12.001, URL https://linkinghub.elsevier.com/retrieve/pii/S0968090X13002581.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transp. Res. Part A: Policy Pract. 77, 167–181. http://dx.doi.org/10.1016/j.tra.2015.04.003, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856415000804.

Fatmi, M.R., Thirkell, C., Hossain, M.S., 2021. COVID-19 and travel: How our out-of-home travel activity, in-home activity, and long-distance travel have changed. Transp. Res. Interdiscip. Perspect. 10, 100350. http://dx.doi.org/10.1016/j.trip.2021.100350, URL https://linkinghub.elsevier.com/retrieve/pii/S2590198221000579.

Fraedrich, E., Lenz, B., Cyganski, R., 2015. Travel-time valuation for automated driving: A use-case-driven study. In: Proceedings of the 94th Annual Meeting of the TRB. 94th Annual Meeting of the Transportation Research Board. Washington DC, URL https://elib.dlr.de/95260/.

Frei, C., Mahmassani, H.S., Frei, A., 2015. Making time count: Traveler activity engagement on urban transit. Transp. Res. Part A: Policy Pract. 76, 58–70. http://dx.doi.org/10.1016/j.tra.2014.12.007, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856414002997.

Gálvez-Muñoz, L., Rodríguez-Modroño, P., Domínguez-Serrano, M., 2011. Work and time use by gender: A new clustering of European welfare systems. Feminist Econ. 17 (4), 125–157. http://dx.doi.org/10.1080/13545701.2011.620975, arXiv:10.1080/13545701.2011.620975.

Gronau, R., 1973. The intrafamily allocation of time: The value of the housewives' time. Amer. Econ. Rev. 63 (4), 634–651, URL https://EconPapers.repec.org/RePEc:aea:aecrev:v:63:y:1973:i:4:p:634-51.

Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. C 78, 37–49. http://dx.doi.org/10.1016/j.trc.2017.01.010, URL https://linkinghub.elsevier.com/retrieve/pii/S0968090X17300177.

Hägerstrand, T., 1970. What about people in regional science? Pap. Reg. Sci. Assoc. 24, pages6–21. http://dx.doi.org/10.1007/BF01936872.

Haghani, M., Bliemer, M.C., Rose, J.M., Oppewal, H., Lancsar, E., 2021a. Hypothetical bias in stated choice experiments: Part I. Macro-scale analysis of literature and integrative synthesis of empirical evidence from applied economics, experimental psychology and neuroimaging. J. Choice Model. 41, 100309. http://dx.doi.org/10.1016/j.jocm.2021.100309, URL https://linkinghub.elsevier.com/retrieve/pii/S1755534521000427.

Haghani, M., Bliemer, M.C., Rose, J.M., Oppewal, H., Lancsar, E., 2021b. Hypothetical bias in stated choice experiments: Part II. conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods. J. Choice Model. 41, 100322. http://dx.doi.org/10.1016/j.jocm.2021.100322, URL https://linkinghub.elsevier.com/retrieve/pii/S1755534521000555.

Harb, M., Xiao, Y., Circella, G., Mokhtarian, P.L., Walker, J.L., 2018. Projecting travelers into a world of self-driving vehicles: estimating travel behavior implications via a naturalistic experiment. Transportation 45 (6), 1671–1685. http://dx.doi.org/10.1007/s11116-018-9937-9, URL http://link.springer.com/10.1007/s11116-018-9937-9.

Hess, S., Rose, J.M., Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. Transp. Res. Part D: Transp. Environ. 15 (7), 405–417. http://dx.doi.org/10.1016/j.trd.2010.04.008, URL https://linkinghub.elsevier.com/retrieve/pii/S1361920910000684.

Hörl, S., Author, C., Erath, A., Axhausen, K.W., 2016. Simulation of autonomous taxis in a multi-modal traffic scenario with dynamic demand. Arbeitsberichte Verkehrs- Raumplanung 16. http://dx.doi.org/10.3929/ethz-b-000118794, URL http://hdl.handle.net/20.500.11850/118794.

Jain, J., Lyons, G., 2008. The gift of travel time. J. Transp. Geogr. 16 (2), 81–89. http://dx.doi.org/10.1016/j.jtrangeo.2007.05.001, URL https://linkinghub.elsevier.com/retrieve/pii/S0966692307000531.

Juster, F., 1990. Rethinking utility theory. J. Behav. Econ. 19 (2), 155–179. http://dx.doi.org/10.1016/0090-5720(90)90009-V, URL https://linkinghub.elsevier.com/retrieve/pii/009057209090009V.

Keseru, I., Heyndels, E., Dat Ton, T., Macharis, C., 2020. Multitasking on the go: An observation study on local public transport in Brussels. Travel Behav. Soc. 18, 106–116. http://dx.doi.org/10.1016/j.tbs.2019.10.003, URL https://linkinghub.elsevier.com/retrieve/pii/S2214367X18301741.

Keseru, I., Macharis, C., 2018. Travel-based multitasking: review of the empirical evidence. Transp. Rev. 38 (2), 162–183. http://dx.doi.org/10.1080/01441647.2017.1317048, URL https://www.tandfonline.com/doi/full/10.1080/01441647.2017.1317048.

Kim, S.H., Mokhtarian, P.L., 2023. Finite mixture (or latent class) modeling in transportation: Trends, usage, potential, and future directions. Transp. Res. B 172, 134–173. http://dx.doi.org/10.1016/j.trb.2023.03.001, URL https://linkinghub.elsevier.com/retrieve/pii/S019126152300036X.

Kim, S.H., Mokhtarian, P.L., Circella, G., 2020. How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. Transp. Res. Part F: Traffic Psychol. Behav. 70, 68–80. http://dx.doi.org/10.1016/j.trf.2020.02.012, URL https://linkinghub.elsevier.com/retrieve/pii/S1369847819309544.

Kim, H., Moon, H., 2022. Heterogeneous attitudes toward autonomous vehicles: evaluation of consumer acceptance of vehicle automation technology using a latent class approach. Technol. Anal. Strateg. Manag. 34 (12), 1402–1417. http://dx.doi.org/10.1080/09537325.2021.1962522, URL https://www.tandfonline.com/doi/full/10.1080/09537325.2021.1962522.

Kolpashnikova, K., Kan, M.Y., 2021. Eldercare in Japan: Cluster analysis of daily time-use patterns of elder caregivers. J. Popul. Ageing 14 (4), 441–463. http://dx.doi.org/10.1007/s12062-020-09313-3, URL https://link.springer.com/10.1007/s12062-020-09313-3.

Kröger, L., Kuhnimhof, T., Trommer, S., 2019. Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. Transp. Res. Part A: Policy Pract. 122, 146–161. http://dx.doi.org/10.1016/j.tra.2018.03.033, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856417301180.

Lanza, S.T., Collins, L.M., 2008. A new SAS procedure for latent transition analysis: Transitions in dating and sexual risk behavior. Dev. Psychol. 44 (2), 446–456. http://dx.doi.org/10.1037/0012-1649.44.2.446, URL http://doi.apa.org/getdoi.cfm?doi=10.1037/0012-1649.44.2.446.

Lee, J., Lee, E., Yun, J., Chung, J.H., Kim, J., 2021. Latent heterogeneity in autonomous driving preferences and in-vehicle activities by travel distance. J. Transp. Geogr. 94, 103089. http://dx.doi.org/10.1016/j.jtrangeo.2021.103089, URL https://linkinghub.elsevier.com/retrieve/pii/S0966692321001423.

Lyons, G., Jain, J., Holley, D., 2007. The use of travel time by rail passengers in great britain. Transp. Res. Part A: Policy Pract. 41 (1), 107–120. http://dx.doi.org/10.1016/j.tra.2006.05.012, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856406000644.

Lyons, G., Urry, J., 2005. Travel time use in the information age. Transp. Res. Part A: Policy Pract. 39 (2–3), 257–276. http://dx.doi.org/10.1016/j.tra.2004.09.004, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856404000977.

Madre, J.L., Axhausen, K.W., Brög, W., 2007. Immobility in travel diary surveys. Transportation 34 (1), 107–128. http://dx.doi.org/10.1007/s11116-006-9105-5, URL http://link.springer.com/10.1007/s11116-006-9105-5.

Magidson, J., Vermunt, J.K., 0000. Latent GOLD, URL https://www.statisticalinnovations.com/latent-gold-6-0/.

Magidson, J., Vermunt, J., 2004. Latent class models. In: Kaplan, D. (Ed.), The Sage Handbook of Quantitative Methodology for the Social Sciences. Sage, pp. 175–198, Pagination: 528.

Mokhtarian, P.L., 1990. A typology of relationships between telecommunications and transportation. Transp. Res. Part A: General 24 (3), 231–242. http://dx.doi.org/10.1016/0191-2607(90)90060-J, URL https://linkinghub.elsevier.com/retrieve/pii/019126079090060J.

Mokhtarian, P.L., 2000. Telecommunications and travel. In: Transportation in the New Millennium. Washington, DC, URL https://onlinepubs.trb.org/onlinepubs/millennium/00115.pdf.

Mokhtarian, P.L., 2018. The times they are A-changin': What do the expanding uses of travel time portend for policy, planning, and life? Transp. Res. Rec.: J. Transp. Res. Board 2672 (47), 1–11. http://dx.doi.org/10.1177/0361198118798602, URL http://journals.sagepub.com/doi/10.1177/0361198118798602.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of dutch travelers. Transp. Res. Part A: Policy Pract. 83, 14–29. http://dx.doi.org/10.1016/j.tra.2015.11.001, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856415002591.

Mullens, F., Glorieux, I., 2022. Dreams versus reality: wishes, expectations and perceived reality for the use of extra non-work time in a 30-hour work week experiment. Commun., Work Family 1–27. http://dx.doi.org/10.1080/13668803.2022.2092452, arXiv:10.1080/13668803.2022.2092452.

Mullens, F., Verbeylen, J., Glorieux, I., 2021. Rethinking the workweek: Results from a longitudinal time-use study of a 30-hour workweek experiment. J. Time Use Res. http://dx.doi.org/10.32797/jtur-2021-4, URL https://jtur.iatur.org/home/article/5c4f2005-8cd8-4a36-bc23-7a9e17be5287.

Nielsen, T.A.S., Haustein, S., 2018. On sceptics and enthusiasts: What are the expectations towards self-driving cars? Transp. Policy 66, 49–55. http://dx.doi.org/10.1016/j.tranpol.2018.03.004, URL https://linkinghub.elsevier.com/retrieve/pii/S0967070X17302937.

Pawlak, J., Circella, G., Mahmassani, H., Mokhtarian, P., 2019. Information and Communication Technologies (ICT), Activity Decisions, and Travel Choices: 20 years into the Second Millennium and where do we go next?. Washington, DC, URL https://onlinepubs.trb.org/onlinepubs/centennial/papers/ADB20-Final.pdf.

Pawlak, J., Polak, J.W., Sivakumar, A., 2017. A framework for joint modelling of activity choice, duration, and productivity while travelling. Transp. Res. B 106, 153–172. http://dx.doi.org/10.1016/j.trb.2017.10.010, URL https://linkinghub.elsevier.com/retrieve/pii/S0191261517306185.

Politis, I., Georgiadis, G., Papadopoulos, E., Fyrogenis, I., Nikolaidou, A., Kopsacheilis, A., Sdoukopoulos, A., Verani, E., 2021. COVID-19 lockdown measures and travel behavior: The case of thessaloniki, Greece. Transp. Res. Interdiscip. Perspect. 10, 100345. http://dx.doi.org/10.1016/j.trip.2021.100345, URL https://linkinghub.elsevier.com/retrieve/pii/S259019822100052X.

Potoglou, D., Whittle, C., Tsouros, I., Whitmarsh, L., 2020. Consumer intentions for alternative fuelled and autonomous vehicles: A segmentation analysis across six countries. Transp. Res. Part D: Transp. Environ. 79, 102243. http://dx.doi.org/10.1016/j.trd.2020.102243, URL https://linkinghub.elsevier.com/retrieve/pii/S1361920919307230.

Primi, A., Marchioro, C., 2020. Time-geography approach during the COVID-19 emergency in Italy: A constraints study at national and local level. J. Res. Didact. Geogr. 2 (9), 97–112. http://dx.doi.org/10.4458/3617-09.

Pudane, B., 2020. Departure time choice and bottleneck congestion with automated vehicles: Role of on-board activities. Eur. J. Transp. Infrastruct. Res. 306–334. http://dx.doi.org/10.18757/EJTIR.2020.20.4.4801, URL https://journals.open.tudelft.nl/ejtir/article/view/4801, Artwork Size: 306-334 Pagina's Publisher: European Journal of Transport and Infrastructure Research, Pagina's.

Pudāne, B., Molin, E.J., Arentze, T.A., Maknoon, Y., Chorus, C.G., 2018. A time-use model for the automated vehicle-era. Transp. Res. C 93, 102–114. http://dx.doi.org/10.1016/j.trc.2018.05.022, URL https://linkinghub.elsevier.com/retrieve/pii/S0968090X18307277.

Pudāne, B., Rataj, M., Molin, E.J., Mouter, N., van Cranenburgh, S., Chorus, C.G., 2019. How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transp. Res. Part D: Transp. Environ. 71, 222–235. http://dx.doi.org/10.1016/j.trd.2018.11.014, URL https://linkinghub.elsevier.com/retrieve/pii/S1361920918303109.

Pudāne, B., van Cranenburgh, S., Chorus, C.G., 2021. A day in the life with an automated vehicle: Empirical analysis of data from an interactive stated activity-travel survey. J. Choice Model. 39, http://dx.doi.org/10.1016/j.jocm.2021.100286, URL https://linkinghub.elsevier.com/retrieve/pii/S1755534521000191.

Pudane, B., van Cranenburgh, S., Chorus, C., 2021. A day in the life with an automated vehicle: Supporting data and software. http://dx.doi.org/10.4121/14125880.v1, URL https://data.4tu.nl/articles/dataset/A_Day_in_the_Life_with_an_Automated_Vehicle_Supporting_Data_and_Software/14125880/1.

Rahimi, A., Azimi, G., Asgari, H., Jin, X., 2020. Adoption and willingness to pay for autonomous vehicles: Attitudes and latent classes. Transp. Res. Part D: Transp. Environ. 89, 102611. http://dx.doi.org/10.1016/j.trd.2020.102611, URL https://linkinghub.elsevier.com/retrieve/pii/S1361920920307975.

Schwanen, T., Kwan, M.P., 2008. The internet, mobile phone and space-time constraints. Geoforum 39 (3), 1362–1377. http://dx.doi.org/10.1016/j.geoforum.2007.11.005, URL https://linkinghub.elsevier.com/retrieve/pii/S0016718507001790.

Sheela, P.V., Mannering, F., 2020. The effect of information on changing opinions toward autonomous vehicle adoption: An exploratory analysis. Int. J. Sustain. Transp. 14 (6), 475–487. http://dx.doi.org/10.1080/15568318.2019.1573389, URL https://www.tandfonline.com/doi/full/10.1080/15568318.2019.1573389.

Shin, K.J., Tada, N., Managi, S., 2019. Consumer demand for fully automated driving technology. Econ. Anal. Policy 61, 16–28. http://dx.doi.org/10.1016/j.eap.2018.10.002, URL https://linkinghub.elsevier.com/retrieve/pii/S0313592618301048.

Singleton, P.A., 2019. Discussing the "positive utilities" of autonomous vehicles: will travellers really use their time productively? Transp. Rev. 39 (1), 50–65. http://dx.doi.org/10.1080/01441647.2018.1470584, URL https://www.tandfonline.com/doi/full/10.1080/01441647.2018.1470584.

Society of Automotive Engineers, 2018. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. http://dx.doi.org/10.4271/J3016_201806.

Sundo, M.B., Fujii, S., 2005. The effects of a compressed working week on commuters' daily activity patterns. Transp. Res. Part A: Policy Pract. 39 (10), 835–848. http://dx.doi.org/10.1016/j.tra.2004.06.001, URL https://linkinghub.elsevier.com/retrieve/pii/S0965856405000285.

Susilo, Y.O., Lyons, G., Jain, J., Atkins, S., 2012. Rail passengers' time use and utility assessment: 2010 findings from great britain with multivariate analysis. Transp. Res. Rec. 2323 (1), 99–109. http://dx.doi.org/10.3141/2323-12, arXiv:10.3141/2323-12.

Thulin, E., Vilhelmson, B., 2007. Mobiles everywhere: Youth, the mobile phone, and changes in everyday practice. Young 15 (3), 235–253. http://dx.doi.org/10.1177/110330880701500302, URL http://journals.sagepub.com/doi/10.1177/110330880701500302.

Timmermans, H., Van der Waerden, P., 2008. Synchronicity of activity engagement and travel in time and space: Descriptors and correlates of field observations. Transp. Res. Rec.: J. Transp. Res. Board 2054 (1), 1–9. http://dx.doi.org/10.3141/2054-01, URL http://journals.sagepub.com/doi/10.3141/2054-01.

van Bladel, K., Bellemans, T., Janssens, D., Wets, G., 2009. Activity travel planning and rescheduling behavior: Empirical analysis of influencing factors. Transp. Res. Rec.: J. Transp. Res. Board 2134 (1), 135–142. http://dx.doi.org/10.3141/2134-16, URL http://journals.sagepub.com/doi/10.3141/2134-16.

Vermunt, J.K., 2010. Latent class modeling with covariates: Two improved three-step approaches. Political Anal. 18 (4), 450–469. http://dx.doi.org/10.1093/pan/mpq025, URL https://www.cambridge.org/core/product/identifier/S1047198700012560/type/journal_article.

Vermunt, J.K., Magidson, J., 2021. How to perform three-step latent class analysis in the presence of measurement non-invariance or differential item functioning. Struct. Equ. Model.: Multidiscip. J. 28 (3), 356–364. http://dx.doi.org/10.1080/10705511.2020.1818084, URL https://www.tandfonline.com/doi/full/10.1080/10705511.2020.1818084.

Wadud, Z., Huda, F.Y., 2019. Fully automated vehicles: the use of travel time and its association with intention to use. Proc. Inst. Civ. Eng. - Transp. 1–15. http://dx.doi.org/10.1680/jtran.18.00134, URL https://www.icevirtuallibrary.com/doi/10.1680/jtran.18.00134.

Yu, X., van den Berg, V.A., Verhoef, E.T., 2022. Autonomous cars and activity-based bottleneck model: How do in-vehicle activities determine aggregate travel patterns? Transp. Res. C 139, 103641. http://dx.doi.org/10.1016/j.trc.2022.103641, URL https://linkinghub.elsevier.com/retrieve/pii/S0968090X22000845.

Zmud, J., Sener, I.N., Wagner, J., 2016. Consumer Acceptance and Travel Behavior Impacts of Automated Vehicles. URL https://static.tti.tamu.edu/tti.tamu.edu/documents/PRC-15-49-F.pdf.